# Early Exposure to Technology and College Major Choice*

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**Abstract**

How does early exposure to coding and robotics influences students' later choice of college major? In this paper, we leverage the national rollout of FIRST robotics across high schools in a two-way fixed effects design to show that attending a high school with a robotics club increases the likelihood that students major in computer science by 1.3 pp. These effects vary significantly by gender: while these programs increase the likelihood that male students go on to major in any STEM course, engineering/computer science, or computer science specifically, there are negative or null effects on female students and students from lower socioeconomic backgrounds. These results suggest that exposure to high school robotics teams do increase interest in engineering and computer science fields, but widen existing gender gaps in take-up of these fields.

**Keywords: College Major Choice, Robotics, High School Curricula, Occupation Choice**

**JEL:I23, J24, J16**

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# 1 Introduction

A recent strand of literature in the economics of education has highlighted the importance of college major choice as a determinant in later-life labor market outcomes — indeed, some work has suggested that this margin of decision may be as impactful as the choice to attend or to complete college at all [Altonji et al., 2012]. Nonetheless, estimates of the elasticity of major choice with respect to future earnings are relatively small, and even accounting for differences in beliefs about post-college earnings and abilities, much of the gender gap in take-up of high-paying majors such as engineering and computer science are unexplained. In this paper, we aim to make progress in unpacking this unexplained portion of preferences for college major by focusing on the role of earlier-life factors in influencing future college major choice.

In particular, we explore one possible driver of students' interest in STEM majors: high school extra-curriculars that introduce students to engineering and coding skills. Because engineering has a particularly rigid course structure and often requires students to declare interest as freshmen, early exposure to coding and building robots through extra-curriculars may make these majors more accessible to students who otherwise would not pursue these majors. We leverage the roll-out of a high school robotics competition, For Inspiration and Recognition of Science and Technology (FIRST) robotics, across high schools to test how attending a high school with a robotics teams impacts students likelihood of majoring in STEM in the future.

The FIRST robotics competition initiated in 1992 and has since grown to include over 3,000 teams from more than 30 countries. We build a database of all robotics teams from 1992 to present and merge it with college transcript data from College and Beyond II, an administrative database of college student record and transcript data for over 1.3 million students from 19 public colleges across seven university systems. Using a two-way fixed effects design, we show that students from schools with robotics teams are 1.3 pp more likely to major in computer science, with larger impacts for students at schools with well-established teams. In the full sample, there are null effects on take-up of engineering majors

and STEM majors more generally.

These null effects hide substantial heterogeneity by student's demographic characteristics. For male students, there is a large and statistically significant impact of attending a high school with a robotics team on take-up of STEM majors (1.9 pp), engineering and computer science majors (1.5 pp), and computer science majors alone (1.1 pp). In contrast, female students have a null or even negative impact of robotics teams on their likelihood of choosing these majors. We also find that students from lower socio-economic backgrounds (i.e., parental income less than $100,000; parents without college degrees) are less likely to select into STEM majors, engineering/computer science majors, and computer science majors alone if they attend a high school with a robotics team. In contrast, there is a null effect on students with higher-income parents and parents with at least a college degree. Taken together, these results suggest that exposure to high school robotics teams does increase interest in technology related majors but only for male students, potentially unintentionally widening the already existing gender gap in interest in engineering and computer science fields.

These results contribute to several strands of economics and education literature. First, this paper is the first to evaluate the impacts of the roll-out of FIRST across high schools on college major choice using administrative college transcript data, rather than small-scale survey based measures. Several studies have assessed the impact of high-school robotics competitions (or comparable initiatives) on participant outcomes such as attitudes toward STEM or information-technology-related fields [Welch and Huffman, 2011, Mason et al., 2011, Jackson et al., 2019][1]. Notably, Meschede et al. [2024b] aim to study the long-run impacts of participation in FIRST competitions by comparing the outcomes of approximately 800 FIRST participants with 450 comparison students. While the authors attempt to match participants with comparisons along observable lines, they are unable to control for selection among unobservables into FIRST participation in the first place. We complement and ex-

[1]See also Anwar et al. [2019] for a broader review of this literature. Beyond robotics initiatives specifically, other papers have also assessed broader high school environments in influencing STEM career choice, including AP class offerings [Long et al., 2012, Conger et al., 2021] and high-school math curricula [Aughinbaugh, 2012]

pand upon this effort through bringing frontier econometric methods to answer the research question and situate our findings relative to theirs later in the paper.

In focusing on STEM outcomes, our paper also speaks to the burgeoning literature on college major choice[2]. Within this literature, economists have documented effects of ability [Arcidiacono, 2004] as well as expected earnings on what fields students choose to study[Wiswall and Zafar, 2015a,b, Conlon, 2021, Conlon and Patel, 2023]), while other research has documented that major choice is sensitive to overall macroeconomic conditions [Blom et al., 2021]. However, there remains a substantial unexplained portion of preferences for college major that forms prior to college matriculation, which has given rise to attempts to understand the pre-college factors that influence college major preferences. Pre-college factors may be particularly important for majors such as engineering which often require students to apply for entry into the engineering program when applying for college and have strict course requirements that make on-time graduation difficult for those who switch into the major mid-college. While some results in this endeavor suggest that high school curricula do not appear to be significant drivers of future STEM career decisions [Darolia et al., 2020], other entries point to parental background [van der Vleuten et al., 2018] and the gender composition of high school teachers [Bottia et al., 2015] playing a meaningful role. In our focus on extracurriculars, we contribute to the ongoing effort to unpack this "black box."

The heterogeneity in effects over gender that we uncover also constitutes a novel entry in the large literature that has attempted to better understand and address large gender-based disparities in STEM interest, which itself plays a meaningful role in the gender earnings gap [Zafar, 2013]. Past work in this area has focused on factors such as the demographics of faculty and teaching assistants [Price, 2010, Carrell et al., 2010, Griffith, 2014, Griffith and Main, 2021] and intergenerational effects [Humlum et al., 2019, Philipp, 2023]. Notably, this literature has highlighted choices made in high school specifically as important drivers of this gap later in the lifecycle [Brenøe and Zölitz, 2020, Card and Payne, 2021, Gurantz, 2021, Granato, 2023]. Engineering and computer sciences are fields within STEM in which

[2]See Patnaik et al. [2020] for a review of this literature

gender gaps are particularly persistent and our work provides new evidence on the role that high school extra-curriculars may play in driving this gap.

The rest of the paper proceeds as follows. In Section 2, we describe the history of FIRST robotics competitions and our data on their expansion. Section 3 describes our empirical approach for estimating the causal impact of robotics competitions on long-term STEM interest, and Section 4 presents our empirical results. Sections 5 and 6 discuss our findings in the context of the broader literature and conclude.

# 2 Data and Policy Setting

## 2.1 FIRST Robotics

FIRST Robotics is an international non-profit founded in 1989 with the goal of encouraging students to enter engineering and technology fields through programs which introduce robotics to high school and middle school students. Their primary program, the FIRST Robotics Competition (FRC), is a program in which teams of high schools students build robots to compete in annual challenges that require the robots to complete tasks such as scoring goals or completing obstacle courses. Students build the physical chassis for a robot, design and maintain the electrical and pneumatic systems, and program the code used to run the autonomous systems in the robot. Most teams are extra-curricular after-school clubs rather than classes, and are guided by both teachers within the high school and industry mentors.

Using publicly available data scraped from the FIRST website's competition archives, we create a panel of team by year information on participation in FIRST. While the original FRC took place in 1992 with 28 teams, it has rapidly expanded in the last thirty years with the most rapid expansion occurring in the mid 2000s. In 2000, there were 372 teams competing in FRC. By 2010, there were 1808 teams including over 45,000 high school students competing in over 53 different competitions. As of 2023, there were 3,304 teams involving over 83,000 high school students in 167 different competitions.

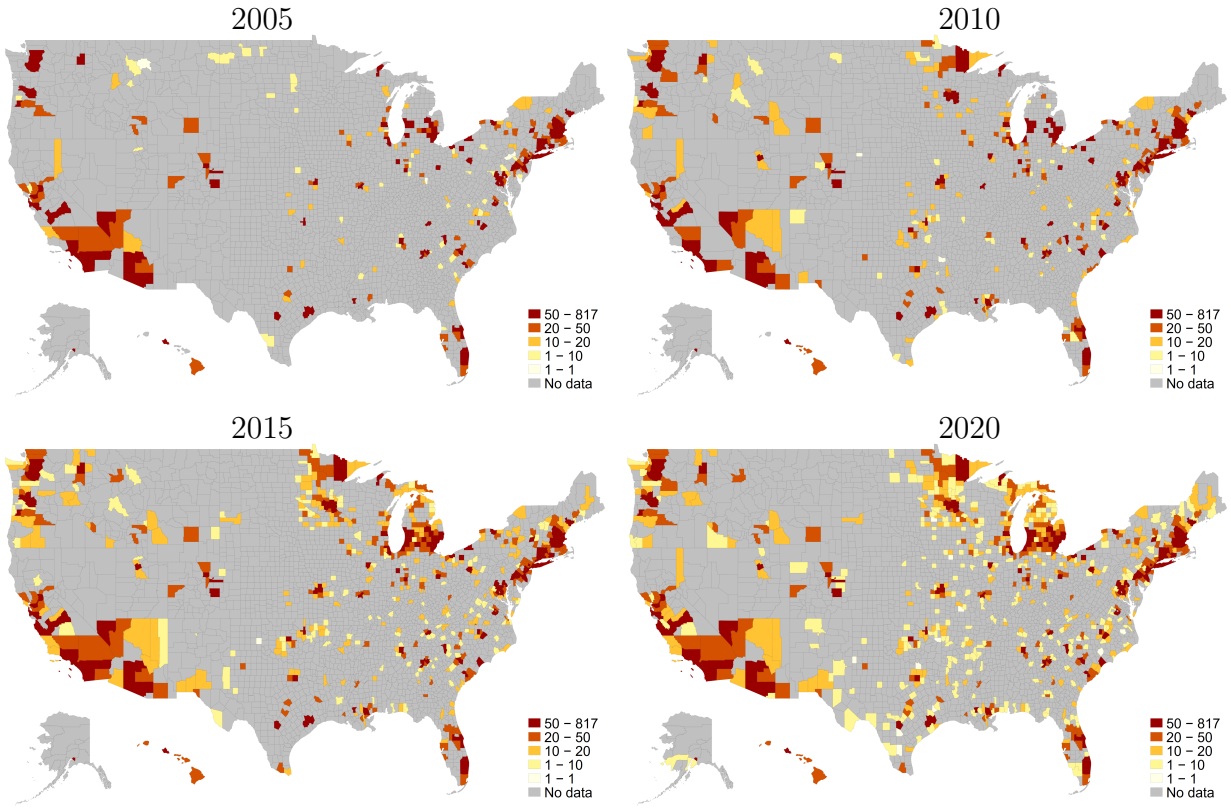



Figure 1: Number of robotics team by county, 2005-2020

Figure 1 shows a heat map of the number of teams per county in 2005, 2010, 2015, and 2020. As shown in the upper left graph, early adoption was concentrated primarily in the Northeastern corridor (Boston-NY-Philadelphia-DC) and in technology/engineering hubs such as Silicon Valley, Seattle, and Detroit. By 2015, the program had spread beyond technological hubs and is fairly wide spread over most regions excluding the less populous states in the Great Plains/ Mountain region (e.g., the Dakotas, Montana, Wyoming)

For each FRC team, we are able to observe the school name(s), city, state, and year that the team originally competed (rookie year henceforth). We create a panel of schools which had a FRC team from 1992 through 2021. Because the data does not include unique identifiers for school name, we use a fuzzy matching algorithm to match school names reported in the raw data set to school names in the database of CEEB codes provided by the College Board. We first drop any teams which do not report a rookie year or report

that they are an international team. We standardize common words (e.g., high school and HS), remove punctuation and stop words, and then match within state on school name to the CEEB database using Stata18 command matchit. In cases where a team has multiple organizations attached to it, we separate the organizations into separate strings and match each organization individually.

Out of 5,803 teams in our scraped database, we are able to get a match to at least one school name for 3,631 or 62.5% of teams. In total, we have 4,116 high schools which ever were associated with an FRC team.[3]

## 2.2 College and Beyond II

Our outcome data comes from the College and Beyond II (CBII), a dataset administered by the Inter-university Consortium for Political and Social Research (ICPSR) including college student record and transcript data for over 1.3 million students from 19 public colleges across seven university systems including the City University of New York system , Georgia College and State University system, Indiana University-Bloomington, Truman State University, University of California-Irvine, University of Houston, and University of Michigan. The data covers all students who attended these universities from 2000 through 2020 and provides information on courses taken, grades, college completion, major and minor choice, demographics (sex, race, citizenship), and pre-college characteristics including pre-college test scores, family income, permanent address zip code, and high school code.

We merge this data with our school-year panel of robotics team data using year of high school entry, measured as four years prior to entry to college, and high school CEEB code when available.[4] In the final data set, we know for each student if they studied in a high school that ever participated to the program, if they entered the school after the program was already in place, and for how many years they were exposed to the competition. We define a student as treated based on the treatment status of their high school in their freshman year

[3]There is a higher number of high schools than teams because a team can be associated with multiple high schools.

[4]CEEB is provided in only two out of the seven university systems.

(i.e., treated for all of high school).

Our primary outcome of interest is student's college major at time of graduation. As we would expect that exposure to robotics extracurriculars increases interest and/or skills in STEM fields, such as computer science or engineering, we create three measures of STEM majors: an indicator for majoring in any STEM field, defined as CIP codes 1, 11, 14, 15, 26, 27, 40, 41, or 51, an indicator for majoring in engineering or computer science, defined as CIP codes 11, 14, or 15, and an indicator for majoring in computer science alone, defined as CIP code 11.[5] In supporting analyses, we look at the impacts on majors we would expect students to be drawn out of, such as humanities majors (CIP codes 5, 16, 22, 23, 24, 25, 38, 39, 50, and 54) and social science majors (CIP codes 4, 9, 10, 91,42, 44, 45, and 52).

# 3 Empirical Methods

We estimate the impacts of high school robotics teams on college majors using a difference-in-difference design, implemented using a staggered two-way fixed effects specification. We use both a static (eqn. 1) and a dynamic event-study framework (eqn. 2)

$$Y_{ist} = \beta \text{FRT}_{s(i),t} + \gamma X_i + \theta_{s(i)} + \delta_t + \alpha_{g(i)} + \varepsilon_{ist} \tag{1}$$

$$Y_{ist} = \sum_{\tau=-16}^{+16} \beta_\tau \mathbb{1}(t = \text{FRT rookie year} + \tau) + \gamma X_i + \theta_s(i) + \delta_t + \alpha_{g(i)} + \varepsilon_{ist} \tag{2}$$

$Y_{ist}$ is a dummy for whether student i who attended high school s and was a high school freshman in year t majored in a given major category. $FRT_{s(i),t}$ is our treatment variable equal to one if school $s$ had a team in year $t$. In the dynamic setting, we include indicators for leads and lags around the school's rookie year with the year prior to the school starting a team as the omitted category. $X_i$ are student level controls including gender, indicators for race dummies, indicators for US citizenship, indicators for parental income above $100

[5] We do not look at engineering majors alone because a subset of the colleges in CBII do not offer engineering majors.

thousand dollars, and indicators for at least one parent having a bachelor's degree. We also include fixed effect for student's high school ($\theta_{s(i)}$), student's graduation cohort ($\delta_t$), and student's home state ($\alpha_{g(i)}$). Standard errors are clustered at the high school level.

To interpret the $\beta$ as causal estimates of the impact of robotics teams on college major choice, it must be the case that students from untreated schools follow similar trends in the pre-period in term of outcomes and that the timing of their high school starting a FRT is uncorrelated with unobserved time-varying determinants of college outcomes. We might be concerned that high schools that perceive greater demand for technology skills, either from the surrounding labor market or from student preferences, are more likely to start a team. For example, earlier adopters of FIRST robotics tended to be in areas with industry partners willing to sponsor school's teams; Michigan has higher rates of FIRST participation in part due to buy-in from the auto industry. While time or location invariant differences will account for cross-sectional time invariant differences or time-invariant high school differences, we also explore whether observable characteristics about students or schools seem to vary with timing of FRT acquisition.

Table 1 reports the results of a regression to test balance in demographic characteristics and high school test scores for students in treated schools relative to those untreated, as well as the mean levels of these characteristics for the untreated. While there are statistically significant differences between treated and untreated students, they are mostly small in actual value relative to baseline. The exception is the proportion of Asian students and the proportion of students whose parents have a BA; treated students are 1.3 pp more likely to be Asian which is 10% higher than the baseline average and they are 2.9 pp more likely to have parents with a college degree (+5.3%).

Next, we look at aggregate economic conditions in the labor markets that teams are located in. For this we use school-level characteristics from 2009-2019 sourced from the Stanford Education Data Archive 5.0 [Reardon et al., 2024] cross-walked to high school CEEB code using crosswalks from [Lyles et al., 2020]. We regress school outcomes (total enrollment, percent white, percent black, percent free or reduced price lunch, rural status,

Table 1: Balance of Student Characteristics: Demographics

| Outcome Variable: | Female | White | Asian | Black | Hisp. | US citizen | Inc. >100k | Missing Inc. | Parent BA |
|---|---|---|---|---|---|---|---|---|---|
| Treated | -0.010** | -0.007* | 0.013*** | 0.001 | -0.010*** | 0.001 | -0.002 | -0.024*** | 0.029*** |
| | (0.004) | (0.004) | (0.003) | (0.002) | (0.002) | (0.002) | (0.005) | (0.003) | (0.003) |
| Constant | 0.543*** | 0.610*** | 0.135*** | 0.057*** | 0.122*** | 0.952*** | 0.451*** | 0.377*** | 0.534*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Mean | 0.537 | 0.595 | 0.136 | 0.0573 | 0.117 | 0.933 | 0.449 | 0.372 | 0.542 |
| $R^2$ | 0.089 | 0.332 | 0.205 | 0.278 | 0.308 | 0.135 | 0.334 | 0.419 | 0.426 |
| N | 177483 | 177483 | 177483 | 177483 | 177483 | 177483 | 110653 | 177483 | 177483 |

Table Notes: This table reports a regression of the outcome variables (dummies for being in demographic group) on an indicator for being treated, along with high school FE, graduation cohort FE, and state FE. Treated means that the student attended a school that had a team in the previous 4 year before college first term. Standard errors clustered at the high school level are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Balance of Student Characteristics: School Level Characteristics

| | (1) Enrollment | (2) % White | (3) % Black | (4) % FRPL | (5) Rural | (6) Charter | (7) Magnet |
|---|---|---|---|---|---|---|---|
| Treated | 12.79** | -0.005*** | 0.004*** | -0.004** | -0.022*** | 0.001 | -0.006 |
| | (5.401) | (0.001) | (0.001) | (0.002) | (0.007) | (0.001) | (0.004) |
| Const. | 865.347*** | 0.638*** | 0.129*** | 0.461*** | 0.423*** | 0.010*** | 0.046*** |
| | (0.762) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) |
| Mean | 866.77 | 0.638 | 0.130 | 0.460 | 0.420 | 0.010 | 0.045 |
| N | 151595 | 151595 | 151595 | 151595 | 151595 | 151595 | 151595 |
| $R^2$ | 0.979 | 0.989 | 0.991 | 0.931 | 0.893 | 0.927 | 0.813 |

Table Notes: This table reports a regression of school-level outcome variables sourced from Stanford Education Data Archive on an indicator for being treated, along with high school FE, year FE, and state FE. Treated means that the school that had a team in the year that the statistic is calculated. Standard errors clustered at the high school level are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

magnet, charter) on an indicator for if the school had a robotics team along with high school, year, and state fixed effects. We see that schools with robotics teams are slightly larger (+1.4% relative to baseline mean), have fewer White students (-0.7%) and more Black students (+3.0%), have more students on free or reduced price lunch (-0.9%), and are more rural (-0.5%). While these differences are statistically significant, they are mostly small relative to the baseline means.

Finally, we also look at ability measures of students in treated school. We run specification 1 with high school GPA, SAT scores, and ACT scores as outcomes. We note that these are outcomes that are potentially impacted by the treatment as they are measured after the

student has or has not had access to a robotics curriculum; if participation in robotics changes performance in high school classes or performance on standardized tests, we may see differences between treated and non-treated students. Nonetheless, this provides a sense of whether the students differ in skills upon entry into college. Table 3 reports the results. There are small positive effects of treatment on ACT scores and null effects on GPA. While statistically significant, the effects on test scores are very small relative to the baseline mean and are not economically meaningful.

Table 3: Balance of Student Characteristics: Pre-College Test Scores

| Outcome | ACT Math | M/ACT Math | ACT Eng. | M/ACT Eng. | GPA standardized | M/GPA stdized |
|---|---|---|---|---|---|---|
| Treated | 0.130*** | 0.026*** | 0.165*** | 0.026*** | 0.003 | -0.006*** |
| | (0.041) | (0.003) | (0.044) | (0.003) | (0.003) | (0.002) |
| Constant | 28.173*** | 0.277*** | 28.525*** | 0.277*** | 3.741*** | 0.060*** |
| | (0.015) | (0.001) | (0.016) | (0.001) | (0.001) | (0.001) |
| Mean | 28.17 | 0.285 | 28.54 | 0.285 | 3.741 | 0.0595 |
| R2 | 0.382 | 0.479 | 0.385 | 0.479 | 0.301 | 0.439 |
| N | 102611 | 144081 | 102608 | 144081 | 135429 | 144081 |

Table Notes: This table reports a regression of the outcome variables (ACT scores and HS GPA; indicators for missing scores) on an indicator for being treated, along with high school FE, graduation cohort FE, and state FE. Treated means that the student attended a school that had a team in the previous 4 year before college first term. Means for all variables are listed. Variables preceded by "M/" indicate Missing and are dummies for if the test score is missing. Standard errors clustered at the school level in parentheses; * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Taken together, these preliminary analyses suggest that while there are small differences in observables, they are not large enough to be economically meaningful. Nonetheless, we control for student's pre-high school characteristics in all specifications. We also use event studies to check that the parallel trend assumption holds. Lastly, to address bias induced in staggered two-way FE models, we report results using the Borusyak et al. [2024] imputation-biased difference-in-difference estimator.

# 4 Results

## 4.1 Impacts on College Major

In Tables 4, 5, and 6, we report present results from regressing indicators for majoring in STEM, engineering or computer science, and computer science alone on indicators for the treatment in our static difference-in-difference specification described in equation 1. We run this first for the full sample (col. 1 and 2.) and then allowing the treatment to vary by gender (col. 3 and 4), parental income (col. 5 and 6), and parental education (col. 7 and 8).

Table 4: Impacts of Attending a HS with a Robotics Team: STEM Major

| | (1) Overall | (2) Overall | (3) Gender | (4) Gender | (5) Income | (6) Income | (7) Parent BA | (8) Parent BA |
|---|---|---|---|---|---|---|---|---|
| Treated | 0.002 | 0.006 | 0.014** | 0.017** | 0.003 | -0.002 | -0.014* | -0.009 |
| | (0.005) | (0.007) | (0.007) | (0.008) | (0.009) | (0.009) | (0.008) | (0.010) |
| Treated X Female | | | -0.026*** | -0.021*** | | | | |
| | | | (0.007) | (0.008) | | | | |
| Income>100K X Treated | | | | | 0.012 | 0.015* | | |
| | | | | | (0.008) | (0.008) | | |
| Parent BA X Treated | | | | | | | 0.021*** | 0.020** |
| | | | | | | | (0.008) | (0.009) |
| Controls | | X | | X | | X | | X |
| R2 | 0.089 | 0.130 | 0.107 | 0.130 | 0.100 | 0.130 | 0.090 | 0.130 |
| N | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 |

Table Notes: This reports regression coefficients for a regression of an indicator variable for majoring in STEM (defined as CIP codes 1, 11, 14, 15, 26, 27, 40, 41, and 51) on an indicator for being treated, along with interactions with indicators for gender, indicators for family income of over 100K income, and indicators for at least one parent having a bachelor's degree. Mean of the outcome variable is 0.325 for untreated students (N=137,294). Treated means that the student attended a school that had a robotics team in the previous 4 year before college first term. All regressions include fixed effects for high school, state, and student's graduation cohort. Odd columns include controls for student gender, race, parental income, parental education, and student citizenship. Standard errors in parentheses clustered at the high school level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In all specifications, there is no significant impact of attending a high school with a robotics team on major choice in the full sample. However, this null result hides substantial heterogeneity in impacts by demographic groups with particularly strong differences by gender. We see a significant positive effect of the treatment on male students on likelihood of choosing a technical major. Male students whose high school has a robotics team are 1.7 pp (2.3%) more likely to major in STEM and 1.5 pp (9.3%) more likely to major in engineering

Table 5: Impacts of Attending a HS with a Robotics Team: Engineering or CS Major

| | (1) Overall | (2) Overall | (3) Gender | (4) Gender | (5) Income | (6) Income | (7) Parent BA | (8) Parent BA |
|---|---|---|---|---|---|---|---|---|
| Treated | 0.000 | 0.003 | 0.014** | 0.016** | -0.004 | -0.009 | -0.013** | -0.015* |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) |
| Female X Treated | | | -0.030*** | -0.025*** | | | | |
| | | | (0.006) | (0.007) | | | | |
| Income>100K X Treated | | | | | 0.019*** | 0.022*** | | |
| | | | | | (0.007) | (0.007) | | |
| Parent BA X Treated | | | | | | | 0.018*** | 0.024*** |
| | | | | | | | (0.007) | (0.007) |
| Controls | | X | | X | | X | | X |
| R2 | 0.096 | 0.162 | 0.151 | 0.163 | 0.099 | 0.163 | 0.097 | 0.163 |
| N | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 |

Table Notes: This reports regression coefficients for a regression of an indicator variable for majoring in Computer Science or Engineering (defined as CIP codes 11, 14, 15) on an indicator for being treated, along with interactions with indicators for gender, indicators for family income of over 100K income, and indicators for at least one parent having a bachelor's degree. Mean of the outcome variable is 0.152 for untreated students (N=137,294). Treated means that the student attended a school that had a robotics team in the previous 4 year before college first term. All regressions include fixed effects for high school, state, and student's graduation cohort. Odd columns include controls for student gender, race, parental income, parental education, and student citizenship. Standard errors in parentheses clustered at the high school level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

or computer science. In contrast, there is a negative coefficient on the interaction between being female and the treatment variable, indicating that attending a high school with a robotics team widens the gender gap in likelihood of majoring in a technical field. Women from high schools with robotics are 2.1 pp less likely than men from similar high schools to major in STEM. If we calculate the treatment effect for women (i.e., the sum of the two coefficients), there is a null effect on STEM major take-up for women. For engineering and computer science, these disparities are even more pronounced with the treatment effect indicating reductions in major take-up relative to other women in high schools without robotics teams. For example, there is a null effect of the treatment on men's take-up of computer science specifications in the specification including demographic controls, but there is a significant, negative effect for women. This indicates that women are approximately 1.6 pp (36%) less likely to major in computer science if their high school has a robotics teams than in the absence of a team.

We also see disparities by family background, though these differences are less stark and only statistically significant at standard levels for engineering and computer sciences majors.

Table 6: Impacts of Attending a HS with a Robotics Team: CS Major

| | (1) Overall | (2) Overall | (3) Gender | (4) Gender | (5) Income | (6) Income | (7) Parent BA | (8) Parent BA |
|---|---|---|---|---|---|---|---|---|
| Treated | -0.001 | -0.004 | 0.009** | 0.005 | -0.008** | -0.010** | -0.007** | -0.012** |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) |
| Female X Treated | | | -0.020*** | -0.016*** | | | | |
| | | | (0.004) | (0.004) | | | | |
| Income>100K X Treated | | | | | 0.011*** | 0.012*** | | |
| | | | | | (0.004) | (0.004) | | |
| Parent BA X Treated | | | | | | | 0.009*** | 0.010*** |
| | | | | | | | (0.004) | (0.004) |
| Controls | | X | | X | | X | | X |
| R2 | 0.063 | 0.093 | 0.081 | 0.093 | 0.071 | 0.093 | 0.063 | 0.093 |
| N | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 |

Table Notes: This reports regression coefficients for a regression of an indicator variable for majoring in Computer Science (defined as CIP codes 11) on an indicator for being treated, along with interactions with indicators for gender, indicators for family income of over 100K income, and indicators for at least one parent having a bachelor's degree. Mean of the outcome variable is 0.041 for untreated students (N=137,294). Treated means that the student attended a school that had a robotics team in the previous 4 year before college first term. All regressions include fixed effects for high school, state, and student's graduation cohort. Odd columns include controls for student gender, race, parental income, parental education, and student citizenship. Standard errors in parentheses clustered at the high school level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Treated students whose parents make more than $100,000 per year are 2.2 pp (11.7%) more likely to major in engineering or computer science and 1.2 pp (24.3%) more likely to major in computer science alone than those whose high school doesn't have a robotics team, whereas students with lower earning parents have a null effect. This interaction with parental income indicates that these programs widen the gap in take-up of STEM majors by parental income. Similar patterns are seen if we measure student socioeconomic backgrounds using parental education rather than income.

Because the roll-out of FRT across school districts is staggered across time, our primary two-way fixed effect specification may be subject to bias if there are heterogeneous treatment effects by event-time. We therefore use the imputation based estimator from Borusyak et al. [2024] which fits the high school and graduation cohort fixed effects using untreated observations, uses these fixed effects to impute a treatment effect for each period, and then takes a weighted sum of these treatment effects to aggregate into a single treatment effect.

Table 7 reports the results of these regressions for the full sample, for men, and for women. The results are broadly consistent with the previous regressions: attending a high

school with a FIRST robotics team primarily increases interest in technology-related majors for men. There statistically insignificant effects on overall STEM major for all groups, but we have a noisy positive coefficient for men and a noisy negative coefficient for women. When we drill down into STEM majors directly related to robotics, we see that men increase take-up of CS/engineering majors by 3.1 pp which is primarily driven by an increase in CS majors of 1.9 pp.

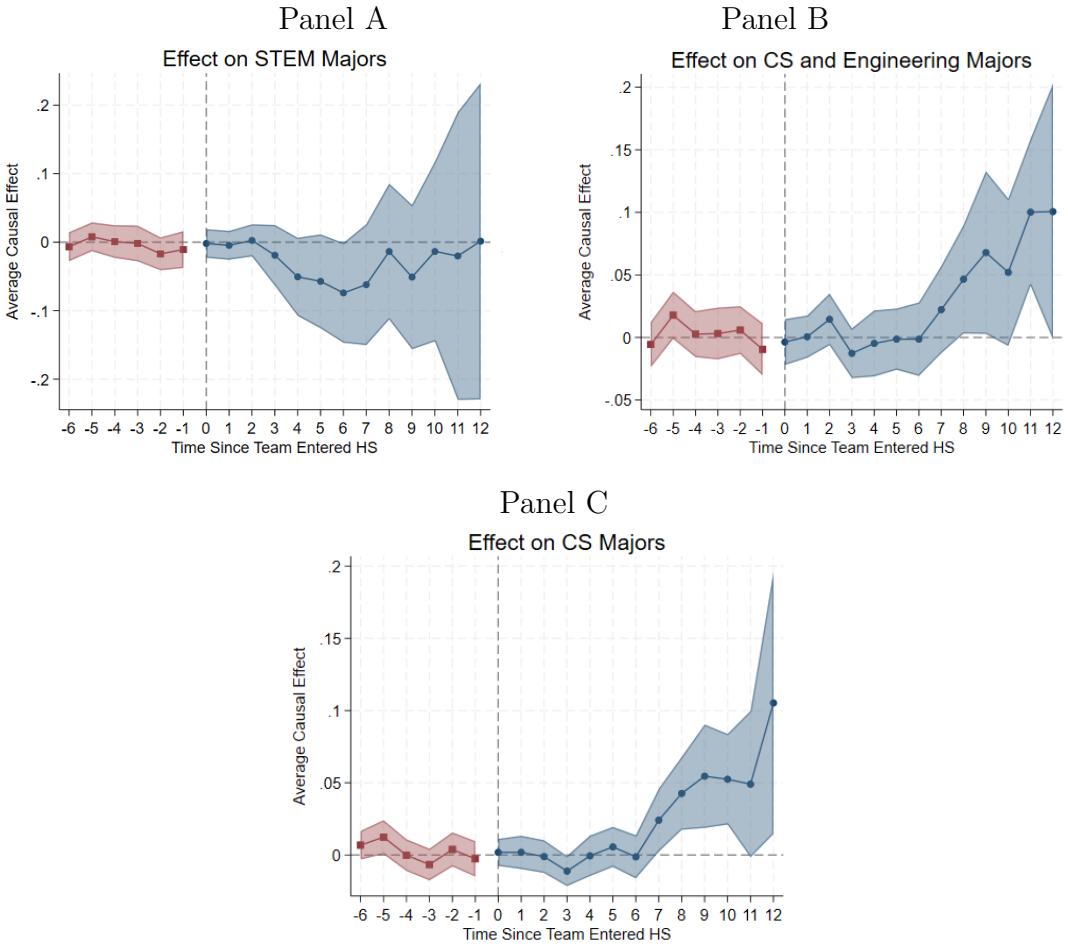
Table 7: Impacts on Major are Robust to Boruysak et al. (2024) Adjustment

| | (1) STEM Major | (2) CS or Engineering | (3) CS |
|---|---|---|---|
| Full Sample | -0.0250 | 0.0129 | 0.0114** |
| | (0.0250) | (0.00997) | (0.00516) |
| N | 97,221 | 97,221 | 97,221 |
| Baseline Mean: | 0.344 | 0.165 | 0.037 |
| Men | 0.0137 | 0.0306* | 0.0190** |
| | (0.0155) | (0.0158) | (0.00829) |
| N | 44,579 | 44,579 | 44,579 |
| Baseline Mean: | 0.420 | 0.269 | 0.065 |
| Women | -0.0314 | -0.00806 | 0.00523 |
| | (0.0263) | (0.00867) | (0.00476) |
| N | 51,965 | 51,965 | 51,965 |
| Baseline Mean: | 0.279 | 0.076 | 0.013 |

Notes. This table reports regression coefficients from regression indicators for major (STEM: CIP 1, 11, 14,15, 26, 27, 40, 41,51; CS or Engineering:11, 14, 15; CS: 11) on the treatment (school having a robotics team) in a bias adjusted regression using the method from Boruysak et al. implemented using Stata program did-imputation. Baseline mean is the average value of the outcome for untreated students. This includes controls for demographics, high school and graduation cohort FE and clusters standard errors at the school level;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We next turn to event study specifications using the dynamic imputation based estimator from Borusyak et al. [2024] to test for parallel pre-trends and explore how timing of a team's entry into a school impacts student's major choice. Given that these robotics teams require

Figure 2: Robotics Teams Increase Likelihood of Majoring in STEM




Notes: This figure reports coefficients 2, our event study regression estimated using imputation adjusted methods from Borusyak et al. [2024], for the outcomes majoring in STEM (panel A), engineering/computer science (panel B), or computer science (panel C). All regressions include fixed effects for high school, state, and student's graduation cohort and controls for student gender, race, parental income, parental education, and student citizenship. 95% confidence intervals included; Standard errors clustered at the high school level.

funding and institutional knowledge which might require some lead time to build up, we might expect that the earlier years of a robotics team are less effective at encouraging students to go into related field. Figure 2 show the results of regressing indicators for majoring in STEM (panel A), engineering/computer science (panel B), and computer science (panel C) on dummies for timing of robotics team entry relative to a student's freshman year of high school, as specified in equation 2.

For all three outcomes, we see parallel trends in the pre-period. We see null effects in the overall sample for STEM majors. For CS and Engineering majors and CS majors alone, we see an increase in likelihood of students choosing technology majors after a delay of about 6 years. Students whose school has had a FRT for eight years when they enter high school are about 5 pp more likely to choose a engineering or CS major, whereas students whose school has had a team for 12 years are approximately 10 pp more likely to choose an engineering or CS major.

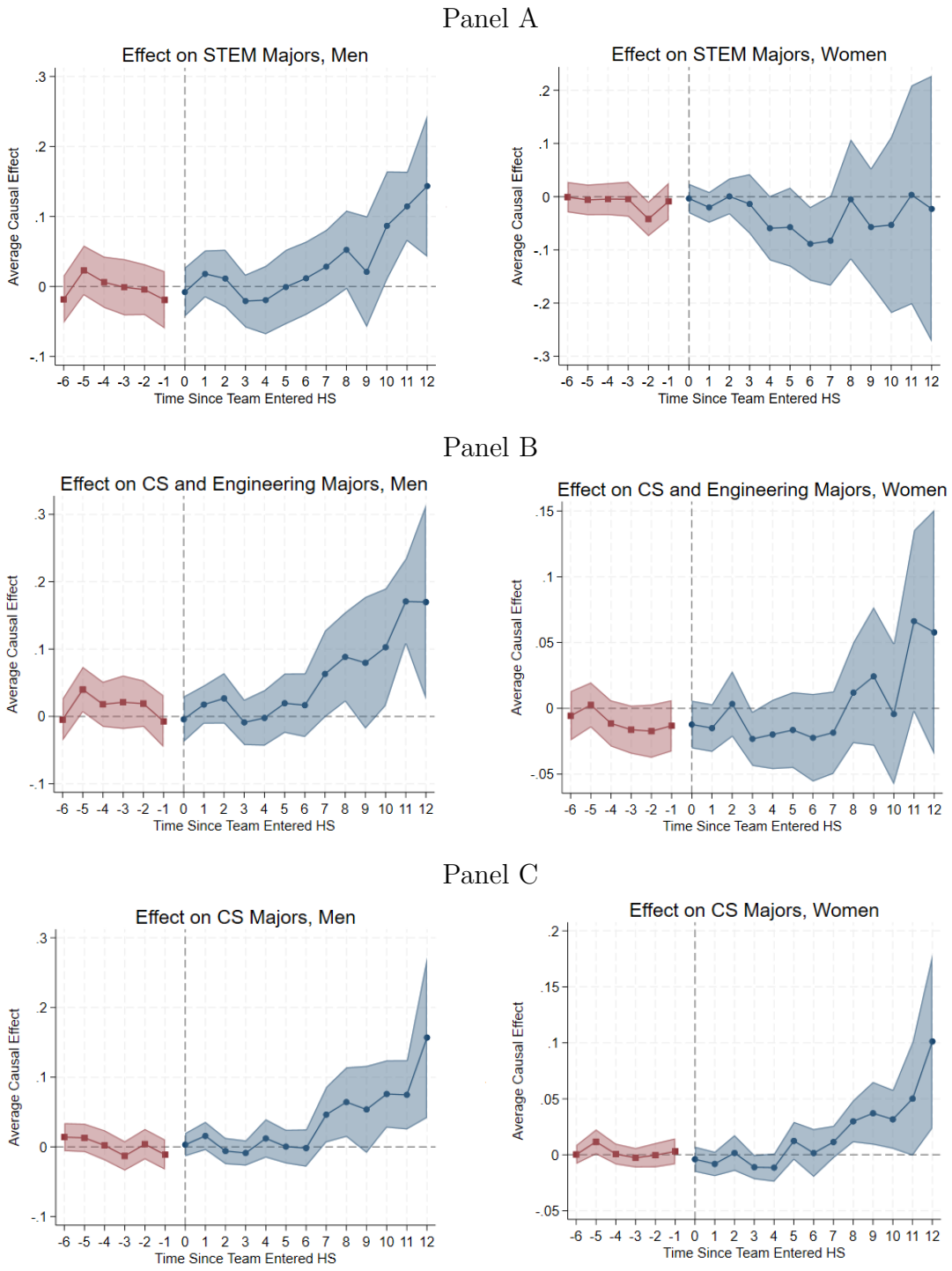
Figure 3 shows the same specifications separately by gender. While the disaggregated time periods are estimated noisily, the patterns are consistent with the results found in the static specification: going to a school with a robotics team increase male student's take-up of STEM majors whereas it has a null or even negative effect on women's take-up. We do see a statistically significant increase in CS majors for both men and women, but the effect sizes for women are approximately half the size of the increases for men.

## 4.2 Impacts on Pre-Major Choice Outcomes

In addition to the effects seen in section 4.1, one might expect that access to FIRST robotics in high school might have intermediate effects that show up prior to deciding on a major. For some students, these extracurricular may induce them to try computer science or engineering courses, but ultimately settle on a different major. We next look at whether attending a high school with a robotics team increases the proportion of credits a student takes within a given field. Courses are categorized as falling within CIP codes and we calculate the percent of all credits that are within STEM as a whole and in engineering and computer science individually. We then regress this on treatment using the same specification as previously. Table 8 reports the results of these regressions, adjusted using the Borusyak et al. [2024] method. There are limited impacts on the proportion of courses taken in these fields with one exception: men triple the proportion of courses in engineering.[6] The lack of effect on

[6]While the null effect on computer science may at first seem at odds with the impacts on majors, many of the courses taken by computer science majors are categorized as engineering classes in the database. While the average proportion of credits that are 'computer science' taken by CS majors is 2.5%, the average

Figure 3: Robotics Teams Increase Likelihood of Majoring in STEM More for Men




Notes: This figure reports coefficients estimated with the method from Borusyak et al. [2024] using equation 2 separately for men (left) and women (right), our event study regression, for the outcomes majoring in STEM (panel A), engineering/computer science (panel B), or computer science (panel C). All regressions include fixed effects for high school, state, and student's graduation cohort and controls for student gender, race, parental income, parental education, and student citizenship. 95% confidence intervals included; Standard errors clustered at the high school level.

STEM courses for men suggest that this is a reshuffling from other STEM courses rather than a shift from non-STEM courses.

Table 8: Impacts of Robotics on Course Choices; Adjusted for Borusyak et al. (2024)

| | (1) STEM courses | (2) CS courses | (3) Engineering Courses |
|---|---|---|---|
| Full Sample | 0.001 | 0.0002 | 0.003 |
| | (0.003) | (0.0005) | (0.003) |
| N | 50,652 | 50,652 | 50,652 |
| Baseline Mean: | 0.234 | 0.006 | 0.047 |
| Men | 0.003 | -0.0006 | 0.009** |
| | (0.004) | (0.001) | (0.004) |
| N | 24,861 | 24,861 | 2,861 |
| Baseline Mean: | 0.250 | 0.073 | 0.007 |
| Women | -0.001 | 0.001 | -0.003 |
| | (0.004) | (0.001) | (0.002) |
| N | 25,540 | 25,540 | 25,540 |
| Baseline Mean: | 0.219 | 0.005 | 0.023 |

Notes. This table reports regression coefficients from regression indicators for proportion of courses in a given field on the treatment (school having a robotics team) in a bias adjusted regression using the method from Boruysak et al. implemented using Stata program did-imputation. This includes controls for high school and graduation cohort FE and clusters standard errors at the school level;* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## 4.3 Where are Students Drawn From?

We next test whether the students entering engineering and computer science majors are drawn from alternative major categories. Table 9 and Table 10 run our primary static specification from equation 1 for the outcomes of majoring in humanities and in the social sciences respectively.

There is a null effect of the treatment on take-up of humanities in the full sample and for male students, but a significant negative impacts on social science majors for men. This

proportion of credits that are 'engineering' is 19.2%.

Table 9: Impacts of Attending a HS with a Robotics Team: Humanities Major

| | (1) Overall | (2) Overall | (3) Gender | (4) Gender | (5) Income | (6) Income | (7) Parent BA | (8) Parent BA |
|---|---|---|---|---|---|---|---|---|
| Treated | -0.002 | 0.004 | -0.007 | -0.004 | 0.003 | 0.005 | -0.004 | 0.006 |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) |
| Female X Treated | | | 0.010** | 0.015*** | | | | |
| | | | (0.005) | (0.005) | | | | |
| Fam. Income > 100K X Treated | | | | | -0.001 | -0.002 | | |
| | | | | | (0.006) | (0.006) | | |
| Parent BA X Treated | | | | | | | 0.004 | -0.004 |
| | | | | | | | (0.005) | (0.006) |
| Controls | | X | | X | | X | | X |
| R2 | 0.088 | 0.098 | 0.092 | 0.098 | 0.090 | 0.098 | 0.088 | 0.098 |
| N | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 |

Table Notes: This reports regression coefficients for a regression of an indicator variable for majoring in Humanities (defined as CIP codes 5, 16, 22, 23, 24, 25, 38, 39, 50, 54) on an indicator for being treated, along with interactions with indicators for gender, indicators for family income of over 100K income, and indicators for at least one parent having a bachelor's degree. Mean of the outcome variable is 0.407 for untreated students (N=116,237). Treated means that the student attended a school that had a robotics team in the previous 4 year before college first term. All regressions include fixed effects for high school, state, and student's graduation cohort. Odd columns include controls for student gender, race, parental income, parental education, and student citizenship. Standard errors in parentheses clustered at the high school level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

effect is of similar size to the positive effect on STEM majors overall for men and suggests that it is not actively in students who were not already inclined towards STEM topics.

For women, there is a positive impact of treatment on take-up of both humanities majors and social science majors. This suggests that exposure to robotics teams in high school not only reduces take-up of engineering and computer science degrees, but it increases the likelihood they pursue non-STEM related majors entirely. This may be driven by female students in these clubs taking on more non-robot-related parts of participating in robotics, such as the fundraising/business team which on average has a greater proportion of female students than the teams focused on building the drive train or coding [Meschede et al., 2024a]. Alternatively, these results could be driven by high school teams being less attractive or welcoming to women as extracurriculars, cementing early on a stereotype that these fields are "for" men.

These results are corroborated in the event studies adjusted using the Borusyak et al. [2024] method; figure 4 reports the effects of team entry into a high school for all students

Table 10: Impacts of Attending a HS with a Robotics Team: Social Sciences Major

| | (1) Overall | (2) Overall | (3) Gender | (4) Gender | (5) Income | (6) Income | (7) Parent BA | (8) Parent BA |
|---|---|---|---|---|---|---|---|---|
| Treated | -0.001 | -0.011 | -0.009 | -0.018** | -0.009 | -0.006 | 0.019** | 0.001 |
| | (0.005) | (0.007) | (0.006) | (0.008) | (0.008) | (0.008) | (0.008) | (0.010) |
| Female X Treated | | | 0.016** | 0.014* | | | | |
| | | | (0.007) | (0.008) | | | | |
| Fam. Income > 100K X Treated | | | | | -0.008 | -0.009 | | |
| | | | | | (0.007) | (0.007) | | |
| Parent BA X Treated | | | | | | | -0.029*** | -0.015* |
| | | | | | | | (0.008) | (0.009) |
| Controls | | X | | X | | X | | X |
| R2 | 0.080 | 0.095 | 0.083 | 0.095 | 0.089 | 0.095 | 0.080 | 0.095 |
| N | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 | 171747 | 106293 |

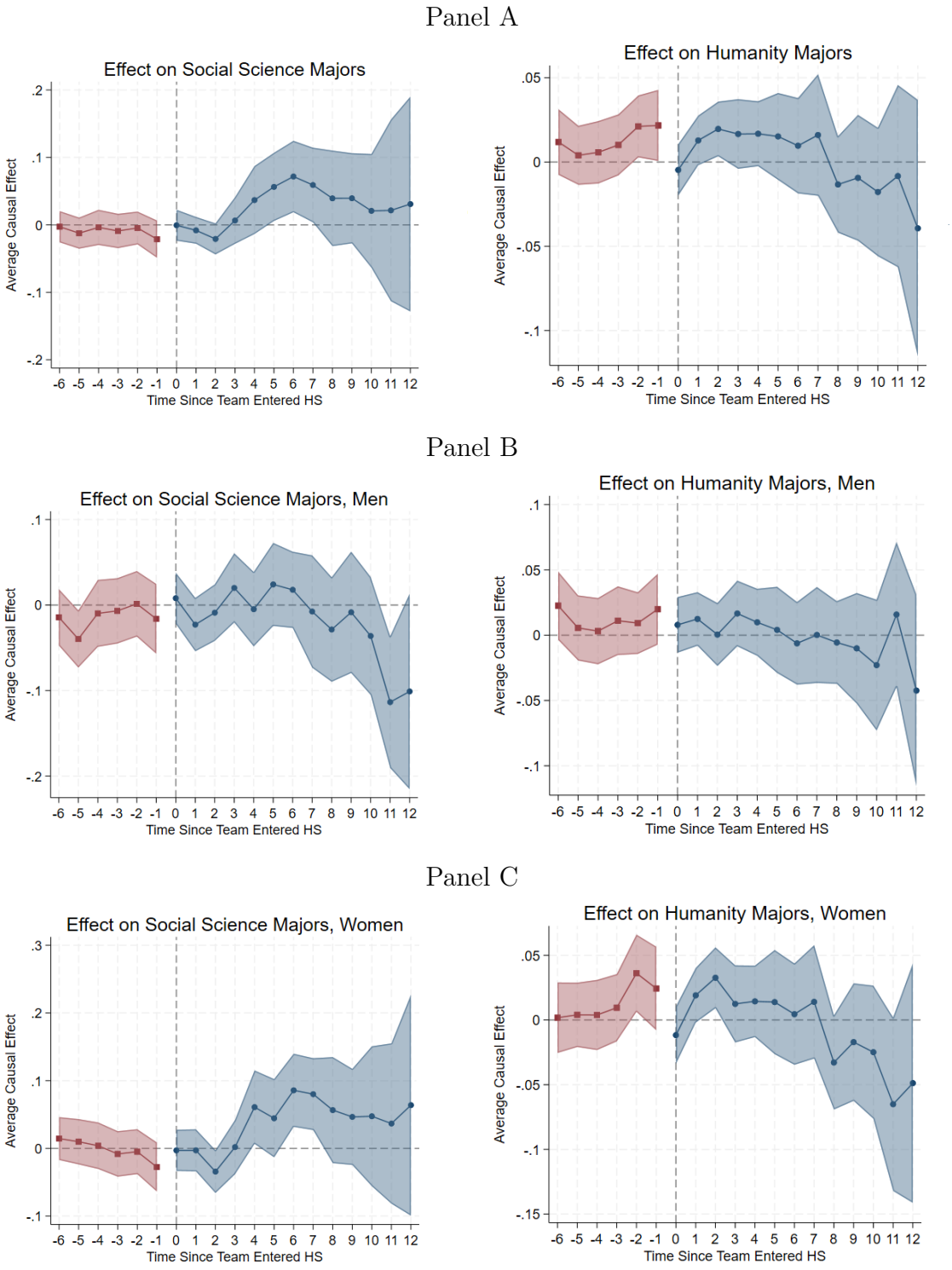
Table Notes: This reports regression coefficients for a regression of an indicator variable for majoring in Social Science (defined as CIP codes 4, 9, 10,19, 42, 44, 45, 52) on an indicator for being treated, along with interactions with indicators for gender, indicators for family income of over 100K income, and indicators for at least one parent having a bachelor's degree. Mean of the outcome variable is 0.407 for untreated students (N=116,237). Treated means that the student attended a school that had a robotics team in the previous 4 year before college first term. All regressions include fixed effects for high school, state, and student's graduation cohort. Odd columns include controls for student gender, race, parental income, parental education, and student citizenship. Standard errors in parentheses clustered at the high school level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(Panel A), men (Panel B), and women (Panel C). Team entry is associated with a 5-8 pp increase in social science majors for women delayed by a similar number of periods as seen for the negative effects on STEM majors in figure 3. The negative effects on social science majorss for men seems to primarily be concentrated many years post- team entry, corresponding to the years with the largest increases in engineering/CS majors. The effects on humanity majors are smaller and non-significant for both genders. Together, these suggest that major shifts induced by high school robotics teams are primarily shifts between STEM and social sciences, rather than humanities.

# 5 Discussion

Our findings suggest that while FIRST robotics was successful in increasing student's interest in engineering and computer science degrees, it may have come at the expense of widening the gender gap in these fields. This contrasts with the findings from the FIRST Impacts longitudinal study Meschede et al. [2024b] which followed the college trajectories of students

Figure 4: Robotics Teams Increase Likelihood of Majoring in SS and Humanities More for Women




Notes: This figure reports coefficients estimated with the method from Borusyak et al. [2024] using equation 2 separately for social science majors (left) and humanities (right), our event study regression, for the the full sample (panel A), men (panel B), or women (panel C). All regressions include fixed effects for high school, state, and student's graduation cohort and controls for student gender, race, parental income, parental education, and student citizenship. 95% confidence intervals included; Standard errors clustered at the high school level.

who participated in FIRST compared to a matched sample of students and found that FIRST increases STEM majors with particularly strong, positive impacts for women. How do we justify these findings?

Rather than look at the effect of participating in FIRST for female students who choose to be in the robotics club during high school, our findings are instead the effect of being in a high school with a robotics team rather than participation, per se. In their comparisons, Meschede et al. [2024b] find that compared to women who do not choose to be on a robotics team, those who do are much more likely to major in STEM. One explanation for the disparities in our findings could be that robotics teams have discouraging effects for female students who do not join the activity in high school due to perception that robotics is a "male" extracurricular. While the authors of the longitudinal study's sample of FIRST students was 68% male, they also surveyed from the same schools a sample of students participating in other science and math extracurriculars which they found to be only 42% male. If male students in our treated schools are more likely to participate in the club than female students in our treated schools, this could explain why the strong treatment effects primarily show up for male students in our sample.

Additionally, there may be differences in male and female students' experiences within the robotics clubs that differentially drive their likelihood of sorting into computer science or engineering majors. As part of the ten-year longitudinal survey [Meschede et al., 2024a], women reported that they felt excluded from the robot building portion of the club, saying "their male peers took over nearly all tasks relating to their team robot, including making adjustments to technical details, driving the robot, and other smaller tasks." Qualitative surveys of participants at robotics competitions find that female students were less involved in programming the robot, even after controlling for prior programming experience [Witherspoon et al., 2016].

We plan to follow-up these analyses by incorporating additional information on gender demographics by school of robotics teams and information on team success in competitions, both of which can be scraped from publicly available websites. These data will allow us

to better understand the mechanisms which explain our findings. For example, if being on a successful team increases take-up of tech majors but being on a less successful team discourages take-up, this could explain both the null results in early years of the team being in the high school and for low-income students. If lower income students are more likely to be one less resourced teams which perform poorly in the regional competitions, we might see less interest in future take-up of the major due to discouragement. Similarly, a student whose high school only added a team a year prior to them entering high school will likely experience a less successful team and not be as inspired to continue with engineering or computer science in college.

# 6 Conclusion

In this paper, we explore how exposure to engineering as a high school student impacts students' likelihood of choosing engineering and computer science related degrees in college. We leverage variation in the roll-out of FIRST robotics teams as an extracurricular at high schools across time to show that attending a high school that has a robotics team increases the likelihood of majoring in computer science by 1.3 pp with larger effects for students at schools with teams that have been established for more than five years.

In addition to overall effects, we also see different effects by gender with strong positive effects of take-up of STEM, engineering, and computer science majors for men in high schools with robotics teams. In contrast, women's take-up of these majors increases less than similarly treated men and there is an overall null effect of high school robotics teams on their likelihood of majoring in technology-related fields. This suggests that early exposure to robotics and technology based extra-curriculars could actually increase the gender gap in participation in engineering, perhaps due to increased salience of gender gaps in the field at earlier stages.

A limitation of our study is that we cannot observe whether a student in our data participated in FIRST robotics or merely attended a high school with a robotics team. This

means that our estimates should be interpreted as the impacts of attending a high school with a team rather than participating in the extra-curricular. These results are therefore a combined effect of actual participating and the effect of seeing others participate while not participating oneself. These potential spill-over effects on non-participants may explain our null/negative effects for women and are consistent with women being less likely to participate in robotics.

In on-going work, we plan to explore heterogeneity by characteristics of the school's robotics program. These analyses will help us pin down the mechanisms driving the changes in major take-up: does attending a high school with a robotics team just increase the likelihood that students try STEM coursework or does it also increase performance in these classes? How does the success of the robotics team in competitions contribute to interest in the field? Taken together, these analyses contribute to our understanding of the so-called 'black box' of preferences for college majors.

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