The Effect of Early College High Schools on STEM degree attainment: Evidence from North Carolina

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Abstract

With growing demand for workers in science, technology, engineering, mathematics (STEM) and healthcare, it is important to assess not only whether education interventions impact educational attainment, but also students' majors. This study examines the impact of Early College High Schools (ECHSs) on Bachelor's degree attainment by field of study using data on 400,000 students from North Carolina (7,300 in an ECHS). Using propensity score weighting, I find ECHSs increase Bachelor's attainment within 10 years of high school entry by 4.7 percentage points (19% over baseline), with STEM degree attainment increasing by 1.3 to 2.4 points (18% to 34%). However, within STEM and STEM-related fields, ECHSs increase degrees in the natural sciences (1.3 points or 45%), math/computer science (0.6 points or 60%), and psychology (1.2 points or 57%), but have null and directionally negative effects on engineering (-0.1 points or -7%) and healthcare (-0.3 points or -17%). Patterns are generally similar across student subgroups, though males drive increases in computer science/mathematics while females and white students drive decreases in healthcare. Thus, ECHSs increase STEM degree attainment overall, but more research is needed to examine whether intensive dual-enrollment experiences like the ECHS may create barriers or disincentives to pursuing certain STEM fields.

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I. Introduction

Over the past fifty years, demand for workers with postsecondary education has steadily risen (Autor 2010; Carnevale and Rose 2015). However, demand varies across field of study, with especially large growth occurring in science, technology, engineering, mathematics (STEM) and healthcare (Dubina et al. 2021; Carnevale and Rose 2015; Zilberman and Ice 2021). Therefore, it is important to examine not only whether educational interventions improve college degree attainment, but also whether they impact students' college majors.

One effort to improve degree attainment is the Early College High School (ECHS). ECHSs are intensive academic programs that help students earn up to two years of college credit or an Associate's degree during high school (Walk 2020). There are now more than 300 ECHSs across at least 30 states, including close to 100 in this study's setting of North Carolina.[1] Research shows that ECHSs greatly increase college degree attainment (Edmunds et al. 2020; Song et al. 2021; Fuller, Lauen, and Unlu 2023). However, no study has examined the impact of ECHSs on students' college majors.

Though ECHSs are general academic programs, they may still impact students' majors, particularly with respect to STEM. For example, many STEM programs "weed out" students who earn low grades in introductory courses (Stinebrickner and Stinebrickner 2014; Witteveen and Attewell 2020; Minaya 2020). As ECHSs improve students' academic readiness (Unlu et al. 2021a; Berger et al. 2013), ECHS students may be more able to complete STEM programs. On the other hand, most ECHS students complete introductory courses through a community college, and many traditional students struggle in STEM after transferring from two- to four-year

[1] This count is based on the author's calculation of the number of schools with "Early College" or "Middle College" in their name in 2020 in the Common Core of Data. Jobs for the Future similarly reported having overseen the implementation of close to 300 ECHSs across 29 states by the early 2010s (Webb and Gerwin 2014).

institutions (Elliott and Lakin 2020). If ECHS students also experience these challenges, ECHSs might unintendedly make it more difficult for students to complete STEM programs.

Therefore, I examine the impact of ECHSs on students' college majors using data from the North Carolina Department of Public Instruction (NCDPI), University of North Carolina (UNC) system, and National Student Clearinghouse (NSC). The data track more than 400,000 students who entered a North Carolina public high school between 2005-06 and 2008-09, 7,300 of whom attended an ECHS. I use propensity score weighting to estimate effects on Bachelor's degree attainment by field of study 10 years after high school entry, focusing on STEM degrees.

I find ECHSs increase the likelihood of earning a Bachelor's degree by 4.7 percentage points (19% over baseline), similar to prior lottery and quasi-experimental studies (Edmunds et al. 2020; Song et al. 2021; Fuller, Lauen, and Unlu 2023). However, growth does not occur evenly across all majors. I find substantial increases in degrees earned in the natural sciences (1.3 points or 45% over baseline), math/computer science (0.6 points or 60%), and psychology (1.2 points or 57%), all of which grew relatively faster than Bachelor's attainment overall. However, I find null and directionally negative effects on engineering (–0.1 points or –7%) and healthcare (–0.3 points or –17%). As a result, overall effects on STEM depend on which majors are counted as "STEM," but range from increases of 1.3 to 2.4 percentage points (18% to 34%) across a selected set of definitions. I observe this same pattern of results within STEM for students who attended ECHSs partnered with two-year and four-year institutions, the latter of which increase Bachelor's attainment by more than 12 percentage points but still produce essentially no increase in engineering or healthcare degrees. I also generally observe this pattern across all student subgroups, though I find that decreases in healthcare are driven by white, female, and higher-achieving students, while the increase in math/computer science is driven by males.

Overall, results show that ECHSs increase STEM and STEM-related Bachelor's attainment, including for students of traditionally underrepresented backgrounds, suggesting that ECHSs can help state policymakers increase and diversify their STEM-educated workforce. However, growth within STEM is uneven, with no growth occurring in the applied fields of engineering and healthcare but large growth in the natural sciences, math, computer science, and psychology. Thus, ECHSs may be causing some students to shift majors within STEM. One reason this might occur is that ECHS students who arrive on four-year campuses as "sophomores" or "juniors" could face challenges or disincentives to accessing healthcare or engineering programs, such as an inability to apply many of their dual-enrollment credits towards the highly-structured four-year curricula often characteristic of these majors, and therefore switch to other STEM fields. Future work should thus further explore whether intensive dual-enrollment experiences may affect students' abilities and incentives to pursue these majors.

II. Background on Early College High Schools

The ECHS emerged in the 2000s as a program designed to ease the transition from high school to college (Walk 2020). ECHSs are open-enrollment schools of choice that primarily target – but are not restricted to – students who are non-white, lower-income, and would be the first generation in their family to attend college. Students enroll in ECHSs in 9th grade and remain for four or five years, during which they take both high school and college courses through a partner college. By high school graduation, students can earn up to two years of college credit or an Associate's degree for free. ECHSs are comprehensive, offering academic and social supports as students begin taking college courses as well as opportunities to reduce the financial and time costs of college via acceleration through introductory coursework for free.

ECHSs were introduced to North Carolina by the North Carolina legislature and a Gates Foundation initiative that funded more than 200 ECHSs across the country in the 2000s (Berger, Adelman, and Cole 2010). North Carolina now has close to 100 ECHSs, present in almost every county in the state (Lauen et al. 2017). ECHSs cost an average of $1,000 more per-pupil per year to operate than traditional schools due to costs associated with providing college-level instruction and managing a college partnership, but their positive impacts on degree attainment have been estimated to make them cost-effective in the long-run (Song et al. 2021).[2]

ECHSs produce several benefits beginning in high school. ECHS students report feeling significantly more engaged and supported by their schools than their peers and experience fewer absences and suspensions (Edmunds et al. 2013; Haxton et al. 2016; Lauen et al. 2017; Unlu et al. 2021a). ECHS students also take an additional 11 college-level courses in high school (Fuller, Lauen, and Unlu 2023; Edmunds et al. 2017). Lottery studies estimate positive effects ranging from 0.05 to 0.14 standard deviation increases in high school English, math, and ACT scores (Berger et al. 2013; Unlu et al. 2021a). About 85 percent of ECHS students graduate high school, a rate similar to their peers (Unlu et al. 2021a; Haxton et al. 2016; Edmunds et al. 2017).

At the postsecondary level, ECHSs produce large impacts on college degree attainment. Two lottery studies find ECHSs increase attainment of any postsecondary credential within 10 years of high school entry by about 11 percentage points from a baseline of 33 percent (Edmunds et al. 2020; Song et al. 2021). However, growth is concentrated at the Associate's level, with a 10 point increase in young adults whose highest degree is an Associate's. For Bachelor's attainment, results are mixed. One lottery study finds no long-run impact, while another finds a 5

[2] One study also shows that ECHSs may increase voting and decrease criminal convictions, adding further social benefits to the ECHS beyond the benefits identified in the previous cost-benefit analysis (Swiderski et al. 2021).

point increase from a base rate of 25 percent (Edmunds et al. 2020; Song et al. 2021).[3] However, studies show significant positive impacts at eight years after high school entry, suggesting that ECHSs at least help some students earn a Bachelor's degree more quickly than they otherwise would have (Edmunds et al. 2020; Song et al. 2021; Fuller, Lauen, and Unlu 2023).

ECHSs may have heterogeneous impacts across student subgroups. Higher-achieving students and students that are not underrepresented minorities, not economically disadvantaged, and who have a parent who earned a college degree experience greater impacts on Associate's attainment than their counterparts (Edmunds et al. 2020; Song et al. 2021; Lauen et al. 2017). At the Bachelor's level, lottery studies have not identified heterogeneity, but this may be due to low power to detect subgroup differences (Edmunds et al. 2020; Song et al. 2021). One study combining quasi-experimental and experimental estimates found stronger effects on Bachelor's attainment for black, economically disadvantaged, and low-achieving students, though this may in part be because these students were more likely to have attended ECHSs that partnered with four-year rather than two-year colleges in this setting (Fuller, Lauen, and Unlu 2023).

No study has examined whether ECHSs affect students' college majors. However, with especially high demand for STEM degrees, students and states need to know whether ECHSs help students access and complete these degrees.

III. Conceptual framework

a) Key predictors of choosing a STEM major

To understand students' college major choices, I draw on the framework of Altonji et al. (2012). This framework proposes that students possess skills, knowledge, and preferences that

[3] Lottery study results in the within-study comparison by Fuller et al. (2023) also show about a 5.5 point increase in Bachelor's attainment at 5 years after high school exit, which is either 9 or 10 years after high school entry for ECHS students and primarily 9 years after high school entry for non-ECHS students.

they aim to match with the skill and knowledge demands and characteristics of educational and occupational pathways to maximize utility. That is, students search for education and career paths that offer the best rewards for their skills, knowledge, and interests. However, choices are made under uncertainty. Students do not fully know their own skills and preferences nor the characteristics of majors and occupations, but can accumulate such knowledge through experience (Morgan et al. 2013; Stinebrickner and Stinebrickner 2014; Bell, Rowan-Kenyon, and Perna 2009). Thus, students may choose STEM when they are interested in math and science, are exposed to STEM, find themselves to be skilled in STEM, and enjoy the wage benefits and non-pecuniary characteristics of STEM majors and careers (see also Wang 2013).

Consistent with this, student interest in math and science is a key predictor of entering STEM (Wang 2013; Weeden, Gelbgiser, and Morgan 2020). Interest may initially be shaped by early experiences, such as discussions and activities with parents (Archer et al. 2012; Maltese, Melki, and Wiebke 2014). By adolescence, interest is related to STEM performance and course-taking (Wang 2013; Kurban and Cabrera 2020). This relationship is reciprocal – students are more likely to take advanced math and science courses when they are interested in STEM, but also report that their interest is sustained by having received good grades in STEM (Maltese, Melki, and Wiebke 2014; see also Avery et al. 2018).

Having high math and science achievement also further improves students' ability to complete a STEM major. Introductory college STEM courses are often characterized by a "grading penalty," in which students earn lower grades than they receive in non-STEM courses (Witteveen and Attewell 2020). Many students initially overestimate their ability to complete a STEM major, and receiving low grades induces many to switch to a different field (Stinebrickner and Stinebrickner 2014; Witteveen and Attewell 2020; Minaya 2020).

There are also disparities in STEM entry by sex, race/ethnicity, and socioeconomic status (Saw, Chang, and Chan 2018; Xie, Fang, and Shauman 2015). While some gaps may be due to differences in achievement, achievement does not fully explain these gaps, especially by gender (e.g., Stearns et al. 2020; Riegle-Crumb, King, and Irizarry 2019). Women, students of color, and low-income students may face other barriers to STEM, including discrimination, a lack of role models, or preferences that are not aligned with the characteristics of STEM occupations and majors (Solanki and Xu 2018; Quadlin 2020; Chang et al. 2011).

b) Effects of ECHS on major choice

Though the ECHSs I examine do not emphasize particular career paths, there are several ways in which they may influence students' major choices. One premise of the conceptual framework is that students base their major choices, in part, on the match between their skills and the skill demands of educational and career paths. ECHSs may affect students' skills and their ability to complete STEM programs in several ways.

First, ECHSs improve students' academic readiness (Unlu et al. 2021a; Berger et al. 2013) and allow students to take introductory courses with supports provided by their high school (Haxton et al. 2016; Edmunds et al. 2013). This could help students complete introductory courses at a higher level of performance, helping them to avoid being "weeded out" and better preparing them to complete intermediate courses after they exit the ECHS.

Additionally, students who enter college with college credits may take more advanced courses, take a wider variety of courses, or double-major (Evans 2019; Gurantz 2021). Thus, accumulating credits in high school could help ECHS students pursue degrees in STEM by providing more time to surmount challenges related to course failure, withdrawal, or scheduling; to have time to explore advanced STEM courses; or to add a STEM double major.

On the other hand, there are reasons why ECHSs may hinder STEM majoring. For one, most ECHSs partner with two-year colleges, such that ECHS students must transfer to a four-year to earn a Bachelor's. Transfer is often associated with academic challenges, especially in STEM (Xu, Jaggars, and Fletcher 2016; Wang 2015). For example, transfer students have not always been taught the same material, in the same way, as their peers at the four-year, which can harm their performance in intermediate courses (Elliott and Lakin 2020). ECHS students could unintendedly be pushed out of STEM if they experience such transfer-related challenges.

Finances are also key to students' educational choices. Students with debt may pursue pathways that are likely to bear higher financial returns to ensure they can pay off their debts. Because STEM is associated with high wages (Wiswall and Zafar 2015), some students may pursue STEM due to financial considerations. Increases in financial aid or decreases in loans can shift students away from STEM and other high-wage occupational pathways (Sjoquist and Winters 2015; Rothstein and Rouse 2011; Schmeiser, Stoddard, and Urban 2016). An unintended consequence of reducing students' college costs could thus be to shift them away from STEM.

These considerations set up two key alternative hypotheses:

Hypothesis 1 – As ECHS students take introductory courses in a setting that provides a high degree of support, improves students' academic readiness, and reduces the time costs of college, ECHSs may increase STEM degree attainment.

Hypothesis 2 – As ECHSs reduce student loans and typically require students to transfer from a community college to pursue a Bachelor's, ECHSs may reduce STEM attainment.

Additionally, not all STEM majors are the same, so ECHSs could produce shifts within STEM. This might especially occur between more specialized and more generalized STEM majors. For example, if ECHSs increase students' likelihood of attending graduate school, students may delay choosing a professional specialization until graduate school and instead pursue a general academic major in undergrad (e.g., Mullen 2010). Engineering and healthcare in particular are also highly structured professional programs that often require separate admissions and high and specific course loads beginning as early as freshman year. If ECHS students earn many credits through dual-enrollment that do not count towards these degrees and wish to enter college with sophomore or junior status reflective of their credits earned, they may be deterred from entering these programs and switch to majors where their credits will apply.

Finally, impacts may also vary across student subgroups by race/ethnicity, sex, economic status, or baseline achievement. Students from backgrounds with more representation in STEM (white, male, high socioeconomic status, and high-achieving) are likely to have more social and cultural resources to support STEM pursuit, such as family that is knowledgeable about STEM and peers and instructors of the same background in STEM (Archer et al. 2012; Solanki and Xu 2018). ECHSs may have relatively more positive impacts for underrepresented students if they compensate for differences in resources that influence STEM participation, but less positive impacts if the resources available to more-advantaged students help them take greater advantage of benefits provided by the ECHS or buffer against any negative impacts of attending an ECHS.

IV. Data

Data for this study come from four sources. First, I use administrative data from NCDPI on 400,000 students (7,300 in an ECHS) who entered 9th grade in a North Carolina public school between 2005-06 and 2008-09. This includes student demographics, academic classifications, course transcripts, and test scores in middle and high school. Second, I use administrative data from the UNC system, available through spring 2020, which include student-level records of institutions attended, dates enrolled, and degree type and field of study. I supplement this with data from the NSC, available through spring 2018, which cover non-UNC institutions. I merged these data using a unique student ID assigned by the state. Finally, in some supplemental analyses I examine effects on Associate's as well as Bachelor's degrees. For these, I include data on Associate's degrees from the North Carolina Community College (NCCC) System, available through spring 2017, which I merged to existing data via name and date of birth matching.

I define treatment as having attended an ECHS in 9th grade. This is comparable to prior propensity score studies and intent-to-treat estimates of prior lottery studies (Edmunds et al. 2020; Song et al. 2021; Unlu et al. 2021a; Fuller, Lauen, and Unlu 2023; Lauen et al. 2017). This is also policy-relevant, as states and districts can open ECHSs but do not require students to complete the program. I define outcomes as whether a student earned a degree in a particular field of study by 10 years after high school entry. I aggregate majors into categories based on CIP codes as listed in Appendix Table A1, focusing on majors within and near to STEM.[4] Traditional STEM includes the natural sciences (biology and physical sciences), math/computer science, and engineering.[5] I also examine healthcare and psychology, which I consider to be "STEM-adjacent" in that they draw large foundations from the natural sciences and can prepare students for high-demand clinical and medical occupations. For reference, I also examine effects on other aggregated fields, including the liberal arts, social sciences, and all other (primarily applied) fields. As some students double-major, categories are not mutually exclusive, but only about five percent of students earn a degree in two different broad categories.

[4] For more information on CIP codes, see: https://nces.ed.gov/ipeds/cipcode/browse.aspx?y=55

[5] I combine physical sciences with biology due to low baseline rates of physical science attainment, and the same for computer science with mathematics. I estimated main results on physical sciences, biology, mathematics, and computer science separately and found similar results within each pair, suggesting that combining the fields does not mask heterogeneity within the group (available on request).

I additionally explore effects on students' high school math and science performance as a potential precursor to STEM attainment using high school transcript data. Outcomes for the transcript analysis include the total number of college-level courses, college-level math and science courses, and math and science courses of any level that a student passed by grade 12; as well as the student's high school GPA and their GPA in math and science courses through grade 12. College-level courses include all Advanced Placement, International Baccalaureate, and dual-enrollment courses. I exclude students missing data on any of these outcomes from the transcript analysis only. This excludes about 10 percent of students from this analysis, such as students who exited the data prior to completing any math or science courses for GPA credit.

I additionally include several pre-treatment (8th grade or middle school) covariates, which include: student race/ethnicity; sex; economic disadvantage (ED; defined by qualification for free or reduced-price lunch); parent education (high school or less, some college, or Bachelor's or higher);[6] mean standardized middle school math and reading test scores;[7] whether the student took Algebra I by 8th grade; mean days absent from 6th through 8th grade; whether the student switched schools during middle school ("mobility"); academically or intellectually gifted status (AIG); disability status; English Learner (EL) status; an indicator of whether the student's 8th grade school was located in a county with no 4-year institution, a UNC institution, or a private four-year institution only; an indicator of the student's 8th grade school urbanicity (rural, town, suburban, or urban); and a 9th grade cohort year indicator.

[6] Parent education was last collected in 2005-06, so I define parent education by their education level in 2006.
[7] I standardized each grade-level score to have a mean of 0 and standard deviation of 1 and average results over 6th through 8th grade. For students not observed in all middle school years, I averaged over the years observed.

I dropped 1 percent of students who were missing demographic data and 1 percent who earned a degree but whose major could not be identified.[8] After this, about 25 percent of students were missing data on at least one covariate – 20 percent have no data on parent education, 10 percent were missing Algebra I course records (mainly in the first cohort), and 5 percent were missing math or reading test scores. I imputed these data using multiple imputation via chained equations (MICE). I included all covariates, the treatment indicator, and outcome variables in the imputation equation and imputed ten datasets (White, Royston, and Wood 2011).[9]

V. Method

a) Primary method

I conducted analysis using propensity score weighting (PSW). I first estimated students' likelihood of attending an ECHS in 9th grade by regressing treatment status on all covariates via a logit model. From this, I produced a predicted value of entering an ECHS, the propensity score (PS). I used the PS to define an average treatment on the treated (ATT) weight, equal to 1 for ECHS students and $\frac{PS}{1-PS}$ for comparisons, to make the comparison group resemble the ECHS group on all covariates. Finally, I included this weight in a regression of the outcome on treatment and all covariates. Including covariates in both steps makes estimates "doubly-robust," such that estimates are unbiased if either the PS or outcome equation is specified correctly (Stuart 2010). I additionally tested sensitivity to instead defining an inverse probability of treatment weight (IPTW) that estimates the average treatment effect (ATE) and to using

[8] Specifically, out of students who earned a Bachelor's, I could not identify the field of study of about 2% of students; out of students who earned an Associate's, I could not identify the field of study of about 3% of students.
[9] Specifically, I include five educational attainment variables in the imputation model: whether the student earned a Bachelor's in STEM/healthcare/psychology; the liberal arts; the social sciences; or another field; and whether the student's highest degree earned was an Associate's in any field. I estimated parent education via an ordered logit, Algebra I via logit, and test scores via OLS using Stata 17's "mi" commands.

regression-adjustment only (i.e., no PS weighting). These alternatives produce similar patterns across key outcomes as the preferred specification (see Appendix Table A2).

I show unweighted and weighted summary statistics in Table 1. ECHS students are disproportionately female, ED, and from less-educated families, but have higher math and reading test scores than non-ECHS students. After weighting, the groups are similar on all characteristics. Formally, I measure the standardized difference, calculated as the difference in means between treatment and comparison groups divided by their pooled standard deviation, i.e.: $d = (\bar{x}_{treat} - \bar{x}_{control}) \Big/ \sqrt{\frac{s^2_{treat} - s^2_{control}}{2}}$ (Austin 2009).[10] Standardized differences greater than 10 percent would indicate imbalance. After weighting, no covariate shows a greater than 3.2 percent difference, and the mean across all covariates is 0.3 percent.[11]

I estimated main effects using the full sample of 9th graders to assess whether ECHSs affect the proportion of young adults who earn a degree in a particular field of study. As most students do not earn a Bachelor's degree, outcomes by field of study are relatively rare, so I estimated models via logit and report exponentiated coefficients (odds ratios). I also report percentage point differences in treatment and comparison marginal rates of attainment.[12]

b) Robustness checks and sensitivity analyses

While prior research on ECHSs includes lottery studies, lottery study data are not useful for the present study because sample sizes would be too small to detect effects on majors.[13] However, while PSW is more powerful, it is also more susceptible to bias. The key assumption

[10] I compute this using the user-written *pstest* command in Stata (Leuven and Sianesi 2003).
[11] Appendix Figure A1 shows that there is also common support across the sample – that is, the range of propensity scores for treatment and comparison students overlaps for almost all students, with no outliers in either group.
[12] I compute this using the user-written *mimrgns* command in Stata (Klein 2014).
[13] A post-hoc power analysis suggests that the largest effects identified in this study would only be detectable in a sample with close to 12,000 lottery students. Lotteries held in the current setting include only about 1,000 students through the 2008-09 cohort and 4,000 through 2010-11 (e.g., Fuller, Lauen, and Unlu 2023; Swiderski et al. 2021).

to interpret estimates as causal is that the model eliminates bias from selection into treatment, including from unobserved variables. Recent within-study comparisons in this setting show that PSW produces similar estimates as lottery studies for many academic outcomes, with estimates on Bachelor's attainment being potentially slightly downwardly biased compared to lottery results, if anything (Fuller, Lauen, and Unlu 2023; Unlu et al. 2021b).[14]

Nevertheless, my estimates could be upwardly biased if there are other confounders that impact whether a student enters an ECHS and their major but not their likelihood of earning a degree generally. STEM interest is a key unobserved variable that could have a strong impact on students' majors. However, as ECHSs do not emphasize a particular career focus, it is unlikely that students select into ECHSs based on STEM interest.[15] Any differences in STEM interest would also be at least partially proxied by observed characteristics like middle school test scores.

I address this further in Sections VI.c and VI.d. In Section VI.c., I estimate effects within one cohort that took a standardized science exam in 8th grade, which proxies for students' STEM interest and ability. I first estimated models in this cohort without the science test score and then re-estimated models with the science score as a covariate to assess the potential extent of omitted variable bias caused by not having this variable available in the full sample. To preview, this covariate reduces the strength of some specific field of study estimates, but this is not strong enough to change any substantive patterns of results.

In Section VI.d., I conduct a sensitivity analysis following VanderWeele and Ding (2017) to estimate the strength of the relationship a potential confounder would need to have with

[14] Importantly, compared to the within-study comparison, I include two additional variables that mitigate downward bias – parent education and an indicator for the presence of a UNC institution in the student's 8th grade county. Each is a negative predictor of entering an ECHS but a positive predictor of earning a Bachelor's and a STEM degree.
[15] I omitted 5 ECHSs enrolling about 700 students that I identified as "STEM" ECHSs. This brought the count of ECHS students in the sample down from 8000 to 7300.

treatment and the outcome to nullify key estimates. I estimate this using the formula $B = \frac{RR_{UD}RR_{EU}}{RR_{UD}+RR_{EU}-1}$, where B refers to the bias that would nullify results, RR_{UD} refers to the risk ratio relationship between the unobserved confounder and the outcome, and RR_{EU} refers to the relationship between the confounder and treatment take-up. These results highlight that lurking confounders would need to be relatively strong net predictors of outcomes, relative to observed variables, and have a moderate impact on ECHS entry to substantively affect results.

VI. Results

a) Effects of ECHSs on high school and short-term college outcomes

I first examine whether ECHSs affect students' short-run math and science outcomes as a potential precursor to STEM Bachelor's degrees. Table 2 shows effects on students' math and science course-taking and performance through grade 12 as well as short-run degree attainment by field of study through Year 6 after high school entry, estimated via the PSW model.

Beginning with high school outcomes, I find ECHS students are significantly more likely to pass at least one college-level course (87.8% vs. 42.5%), passing about 8.3 more by the end of grade 12 relative to a comparison mean of 1.6. ECHS students are also more likely to pass at least one college-level math or science course (55.4% vs. 24.1%), passing about 1.3 more relative to a baseline mean of 0.5.[16] Finally, ECHS students pass nearly 1 additional math and science course (of any level) and have a higher GPA in their math and science courses (0.15 points or a 7% increase), though their overall GPA through grade 12 is the same as their peers.

[16] The most common college math and science courses taken by ECHS students include Introduction to Computers (40% of ECHS students); General Biology I (22%); General Biology II (13%); Precalculus/Algebra (15%); College Algebra (12%); Survey of Mathematics (10%); and Precalculus/Trigonometry (9%). By contrast, the most common college-level math and science courses taken by comparison students are AP Calculus AB (a weighted mean of 11%); AP Environmental Science (9%); AP Statistics (8%); and AP Biology (7%).

The rest of Table 2 shows effects on degree attainment by field of study through Year 6 after high school entry, which offers insight into the Associate's pathways pursued by ECHS students (almost all degrees earned by this point are Associate's). Because many majors have very low counts at the Associate's level, I combined the liberal arts with social sciences and disaggregate STEM and STEM-related fields only into healthcare and non-healthcare.[17] Results show that ECHS students are substantially more likely to have earned a degree by this point compared to peers (28.9% vs 2.0%). There are especially large increases in the proportion of students who earned a degree in the liberal arts/social sciences (primarily "General Studies" degrees, 24.3% of ECHS students vs. 0.7% of comparisons) and non-healthcare STEM (4.3% vs. 0.3%). Put differently, about 80 percent of ECHS students who had earned a degree by this point held a liberal arts or social sciences degree, while 15 percent held a non-healthcare STEM degree, compared to rates of 35 and 15 percent, respectively, among comparison degree earners.

Thus, ECHSs have positive effects on students' math and science performance in high school and increase the percentage of students who complete a STEM Associate's in the short-run, though most ECHS students who earn an Associate's earn a liberal arts degree. These short-run impacts on STEM outcomes could help students to complete STEM degrees in the long-run.

b) Effects on ECHSs on STEM Bachelor's degree attainment

Table 3 shows results on Bachelor's degree attainment by field of study 10 years after 9th grade. Overall, ECHSs increase Bachelor's attainment by 4.7 percentage points, from 24.8 to 29.5 percent (19% over baseline). However, within STEM and STEM-related fields, there is substantial variation. There are large, significant changes in degrees earned in natural sciences

[17] I recoded "General Studies" degrees into their nearest matching category, as possible, based on the degree title. For example, I coded General Studies Biology Pre-Majors as non-healthcare STEM and General Studies Education Pre-Majors as "Other." Because very few (0.4%) of students who earned an Associate's did so in Psychology, I grouped Psychology with other STEM majors for this analysis.

(1.3 points, from 2.9% to 4.2%), math/computer science (0.6 points, from 1.0% to 1.6%), and psychology (1.2 points, from 2.1% to 3.3%). The rate of increase in each of these fields from baseline is 45 to 60 percent, far higher than the growth rate in overall Bachelor's attainment. However, there are null and directionally negative effects on engineering (-0.1 points, from 1.5% to 1.4%) and healthcare (-0.3 points, from 2.1% to 1.8%). That is, although there is a nearly 5 point increase in Bachelor's attainment overall, there is no change or even a slight decrease in the likelihood that a student earns a degree in engineering or healthcare. Estimates on natural sciences, psychology, and math/computer science are significantly different from those on engineering and healthcare.

Given these mixed findings, Table 3 also presents results over three potential definitions of "STEM." By any definition, there are statistically significant increases in STEM attainment, but the magnitude varies. By the first definition – "traditional STEM" (natural sciences, math, computer science, and engineering) – there is a 1.8 percentage point increase (from 5.3% to 7.1%). The second – "STEMM", or STEM plus medical/healthcare – increases by 1.3 points (from 7.4% to 8.7%). Finally, the third – "STEMM plus psychology" – increases by 2.4 points (from 9.5% to 11.9%). The relative increase from baseline for "STEMM" is about 18 percent, similar to the increase in overall Bachelor's attainment. The relative increase from baseline for the other two definitions are somewhat higher than the increase in Bachelor's attainment.

For reference, Appendix Table A3 estimates changes in the distribution of majors among degree earners. This shows that ECHS degree earners are significantly more likely to have majored in the natural sciences, math/computer science, and psychology, but are significantly less likely to have majored in engineering and healthcare. Decreases in engineering and healthcare and increases in natural sciences and math/computer science largely cancel out. As a result, there is no significant change in the likelihood that a degree earner majored in "STEMM." However, ECHS degree earners are about 3 percentage points more likely to have majored in STEM when defined as "traditional STEM" or "STEMM plus psychology."

Finally, Table 4 shows results on three other major categories. ECHSs increase attainment of social sciences degrees by 0.9 points (from 2.2% to 3.1%); liberal arts degrees by 1.0 point (from 4.8% to 5.8%), and all "other" degrees by 1.3 points (from 10.2% to 11.5%).[18]

c) Robustness check using 2009 cohort

Students in the 2009 cohort took a standardized science test in 8th grade, which may proxy for baseline science skills and interests beyond other observed covariates. Therefore, I re-estimated models restricted to this cohort to assess the possible extent of bias that arises from not having access to a measure of pre-treatment science skills in the full sample.[19] I ran models for this cohort without and then with this variable to examine the extent to which estimates changed, though results should be interpreted cautiously given that they are based on only one cohort and are thus more imprecise. Given that the main results showed significant shifts within STEM, I especially aimed to assess whether lacking science achievement scores in the full sample could confound this pattern of results. Appendix Table A5 shows the results. Model 1 reproduces the full results; Model 2 shows results for the 2009 cohort when omitting science scores; and Model 3 shows results for this cohort when including science scores.

Comparing Models 1 and 2 shows that estimates for the 2009 subsample vary somewhat from the main model but show the same pattern of results, especially within STEM. Comparing

[18] Appendix Table A4 shows estimated effects on field of study of the highest degree earned by Year 10 after high school entry. These results show much stronger impacts on liberal arts or social science degrees, largely due to students whose highest degree was an Associate's. Results otherwise show a similar pattern of positive impacts on non-healthcare STEM degrees but a null and directionally negative effect on healthcare degrees.
[19] I drop about 6 percent of students in this cohort who are missing this variable.

Models 2 and 3, the estimate on math/computer science attainment decreases by 14 percent from its baseline odds ratio after controlling for science achievement (i.e., from an increase in the odds of 48.4% in Model 2 to 43.8% in Model 3), the estimate on natural sciences decreases by 10 percent, and the estimate on engineering decreases by 16 percent. Estimates on healthcare and psychology are essentially unchanged. Applying these factors to the main results, a simple approximation would suggest, for example, that the true relative rate of increase in natural sciences if science scores could be observed in the full sample might be around 41 percent rather than 45 percent, while the true rate in math/computer science might be 52 percent rather than 60 percent. In terms of aggregated effects, the rate on traditionally-defined STEM might be 29 percent rather than 34 percent, while the effect in "STEMM" might be 14 percent rather than 18 percent. Therefore, while baseline science scores do modestly affect some estimates, changes are not substantive enough to threaten any main pattern of results.

d) Sensitivity analysis

I next conduct a sensitivity analysis using the method of VanderWeele and Ding (2017), in which I examine the extent to which main estimates would change under different degrees of bias. I show this for the natural sciences and engineering in Table 4. I highlight bias factors that would cause these estimates to have a true risk ratio of between 1.2 and 1.3, similar to the estimated risk ratio on overall Bachelor's attainment of 1.25.[20] For context, I also obtained the risk ratio relationship between having above-average math achievement (relative to below-average) and above-average science achievement with natural sciences attainment from the 2009 subsample estimates.[21] The net risk ratio relationships for these variables were 3.0 and 1.5,

[20] I translated odds ratio to risk ratios using the formula $RR = \frac{OR}{(1-P_{ref})+(P_{ref}*OR)}$, where P_{ref} refers to the probability of the outcome in the comparison group, equal to 51.4% in this case (Zhang and Yu 1998).

[21] I obtained these estimates from a slightly modified model where these variables were dichotomized rather than continuous in order to obtain more interpretable risk ratio estimates for these covariates.

respectively. I note that, descriptively, students with high math achievement were 6 times more likely to earn a natural sciences Bachelor's (5.4% vs. 0.9%) and students with high science achievement were 3.5 times more likely (5.2% vs. 1.5%) in the ATT-weighted sample in this cohort. This highlights the importance of considering the strength of potential confounders net of their likely correlations with covariates that are already included in the model.

Beginning with natural sciences, the true estimate would be reduced to a risk ratio of 1.2 if there was a confounder that increased the likelihood of earning a natural sciences degree by 50 percent (similar to effect of science test scores) and doubled the likelihood that a student entered an ECHS, or if there was a confounder that tripled the net likelihood of earning a natural sciences Bachelor's (similar to the effect of math test scores) and increased the likelihood of entering an ECHS by 30 to 40 percent. Reducing natural sciences to a null effect would require a confounder that tripled the net likelihood of earning a natural sciences Bachelor's and doubled the likelihood of entering an ECHS. For engineering, the true estimate would be a risk ratio of 1.2 if there was a confounder that halved the likelihood of earning an engineering Bachelor's and increased the likelihood of entering an ECHS by 60 percent, or a confounder that reduced the likelihood of earning an engineering degree by a third and increased the likelihood of entering an ECHS by 20 percent. Thus, a confounder with net strength equal to the most impactful observed variables would still need to have a substantive relationship with treatment take-up to explain away results.

Further, to explain the pattern of results observed across STEM fields, there must either be a confounder that explains both the shift into natural sciences (and math/computer science) and away from engineering (and healthcare) or multiple confounders that separately explain these effects. In Appendix C, I conduct an alternative sensitivity analysis in which I aim to directly assess whether a confounder could explain away this pattern of results within STEM. I find that a confounder would need to have a much stronger impact on which STEM major a student chose than any observed variable to be able to explain away this pattern of results.

e) Subgroups effects on STEM Bachelor's degree attainment

Table 5 shows results across student subgroups by race/ethnicity, sex, economic disadvantage, and baseline math achievement, as well as by the level of the ECHSs' postsecondary partner (two-year or four-year).[22] I first note that I find stronger effects on overall Bachelor's attainment for traditionally underrepresented student subgroups. Changes in the odds are significantly stronger for black/Hispanic than white students and ED than non-ED students, though these results may relate to the fact that many four-year historically black colleges and universities (HBCUs) hosted ECHSs in this setting. Indeed, consistent with prior research, I also find that ECHSs partnered with four-year institutions have substantially more positive impacts on Bachelor's attainment than ECHSs partnered with two-year institutions (Lauen et al. 2017; Fuller, Lauen, and Unlu 2023).

In general, I find the overall pattern across STEM fields – stronger positive effects in the natural sciences, math/computer science, and psychology than engineering and healthcare – to be present for all subgroups, though many estimates are imprecise. Notably, this pattern even occurs in the sample of students who attended ECHSs partnered with four-year institutions. These ECHSs increased Bachelor's attainment by 12.4 percentage points (from 37.2% to 49.6%). They produced a 3.9 point increase in the natural sciences (from 4.8% to 8.7%), a 1.9 point increase in math/computer science (from 1.8% to 3.7%), and a 1.6 point increase in psychology (from 3.5%

[22] I reweighted subsamples by conducting the first-stage PS equation using only students in the subgroup. Baseline math samples are restricted to students with observed (not imputed) test scores. Key balance statistics are shown in Appendix Table A6. Subgroup results on the three selected definitions of STEM are shown in Appendix Table A7.

to 5.1%). However, they had essentially no impact on engineering (increased from 2.6% to 2.8%) and a directionally negative impact on healthcare (from 2.7% to 2.5%).

Additionally, although differences between other subgroups are generally not statistically significant, there are a few places where estimates between subgroups appear to differ. For one, relative changes in natural sciences degrees are especially large for students of underrepresented backgrounds. The marginal rate of natural science Bachelor's attainment nearly doubled from 1.9 to 3.7 percent for Black/Hispanic students, but increased from just 2.9 to 3.6 percent for white students. Thus, the racial/ethnic gap in natural sciences degree attainment closed completely among ECHS students. By ED status, the rate of growth in natural sciences was larger for ED students (from 1.6% to 2.7%) than non-ED students (from 3.9% to 5.5%), but the gap between ED and non-ED students grew in absolute magnitude. A similar pattern occurred by baseline achievement, where students in the middle third of the baseline achievement distribution doubled their likelihood of natural sciences attainment (from 1.1% to 2.2%), but students in the top third experienced larger absolute growth (from 5.2% to 6.9%). These results should be interpreted within the context that underrepresented students experienced larger impacts on degree attainment overall and more commonly attended four-year-partnered ECHSs.

Additionally, increases in computer science/math degrees were entirely driven by male students, whose likelihood of attaining these degrees increased from 1.6 to 3.1 percent, whereas for females it rose from just 0.6 to 0.7 percent. Meanwhile, decreases in healthcare were driven by white, female, and top-achieving students, whereas their counterparts experienced no changes or even slight increases in attainment of these degrees.

VII. Discussion

This study first shows that ECHSs increase STEM Bachelor's degree attainment. Depending on the definition of STEM used, ECHSs produce 1.3 to 2.4 percentage point increases in STEM Bachelor's attainment, ranging from 18 to 34 percent increases over baseline, relative to a 19 percent increase in Bachelor's attainment overall. However, this study also shows that STEM-related growth is driven by increases in the natural sciences, math/computer science, and psychology, whereas there are no changes or even slight decreases in engineering and healthcare.

One interpretation of these results is that ECHSs increase degree attainment generally, do so at least as much or more so for students interested in pursuing STEM, but cause some students to shift their majors within STEM. While I cannot discern with certainty why ECHSs may shift students out of engineering and healthcare, one possibility is that ECHS students who enter four-year institutions as "sophomores" or "juniors" face structural barriers or disincentives to entering these professional programs, which often have highly structured and intensive four-year course sequences and separate, competitive admissions within a university. Entering these programs could limit students' ability to make use of general education dual-enrollment credits and require students to enroll with "freshman" status that is not reflective of their prior credits earned, which could lead some to prefer to switch to a major where their credits will count towards major requirements and allow them to graduate more quickly. This explanation appears especially plausible given that most ECHS students who earn an Associate's degree in the short-run do so in the liberal arts and that ECHS students at four-year partnered ECHSs also experienced null or negative impacts on engineering and healthcare despite experiencing very large growth in Bachelor's attainment.

Because of the mixed pattern of results within STEM, the extent to which ECHSs increase “STEM” attainment depends somewhat on the definition of STEM used. Under a traditional definition that excludes healthcare, there is a substantial increase. However, as there is currently high demand for healthcare professionals, and as it is likely that some students switch between healthcare and the natural sciences, a definition that includes healthcare is likely more useful. Less clear is the placement of psychology, which is often not counted as STEM but which might also be an alternative option for students in the natural sciences or healthcare and can lead to high-demand clinical careers, particularly when taken as a Bachelor of Science degree. In any case, ECHSs increase “STEM” attainment, with growth in STEM close to proportional to (or slightly higher than) growth in Bachelor’s attainment overall. This suggests that changes in concentrations within STEM fields are likely primarily due to students switching which field of STEM they choose to pursue rather than switching into or out of STEM.

A primary limitation of this study is its dependence on the selection-on-observables assumption. However, a recent within-study comparison found that propensity score estimates in this sample were similar to and actually slightly underestimated ECHS impacts on Bachelor’s attainment, suggesting that my estimates may be somewhat conservative (Fuller, Lauen, and Unlu 2023). My estimates may also be conservative in that they estimate the effect of attending an ECHS rather than of completing an ECHS program. Via a sensitivity analysis, I found that a confounder would need to have impacts on the outcome that are as large as some of the strongest predictors observed and be at least moderately associated with ECHS entry to nullify the key pattern of results identified. One of the most likely confounders might have been baseline science skill and interest, yet I find that pre-treatment science test scores did not have sufficient strength to substantively affect results in a subsample for whom these scores were available.

Overall, this study shows that ECHSs increase STEM Bachelor's attainment, including and especially for students of traditionally underrepresented backgrounds, suggesting that ECHSs can help policymakers achieve goals of expanding and diversifying the STEM-credentialed workforce. However, growth within STEM is uneven, with some students likely switching out of engineering or healthcare and into natural sciences, math, computer science, or psychology. Education leaders and researchers should therefore further explore whether and how intensive dual-enrollment pathways might affect students' access or incentives to enter certain applied STEM programs.

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Tables

Table 1

Descriptive and balance statistics

		ATT Weighted		Unweighted	
	ECHS	Comp	Std Diff (%)	Comp	Std diff (%)
Male	0.40	0.40	0.0	0.51	22.5
White	0.56	0.56	0.0	0.57	1.3
Black	0.27	0.27	0.2	0.30	6.2
Hispanic	0.09	0.08	0.3	0.07	4.7
Asian	0.03	0.03	0.0	0.02	8.4
Am. Indian	0.02	0.02	0.0	0.01	3.9
Multi-racial	0.03	0.03	0.1	0.02	2.2
Econ. Disadvantaged	0.50	0.50	0.1	0.44	12.6
Parent: High school or less	0.46	0.44	3.2	0.38	16.4
Parent: Some college	0.26	0.26	0.5	0.25	3.8
Parent: Bachelor's or more	0.23	0.24	1.9	0.30	16.7
Middle school math avg	0.31	0.30	0.3	-0.02	36.3
	(0.82)	(0.91)		(0.97)	
Middle school reading avg	0.34	0.33	0.3	-0.03	41.7
	(0.77)	(0.85)		(0.97)	
Middle school took Alg I	0.26	0.26	0.4	0.18	17.4
Disability	0.05	0.05	0.2	0.13	28.1
AIG	0.20	0.20	0.2	0.16	10.3
LEP	0.04	0.04	0.3	0.05	2.6
Middle school mobility	0.19	0.19	0.1	0.16	9.4
Middle school absence avg	7.38	7.38	0.1	8.09	10.2
	(6.16)	(6.52)		(7.67)	
Urban	0.15	0.15	0.1	0.24	21.8
Suburban	0.12	0.12	0.0	0.16	11.0
Town	0.18	0.18	0.2	0.13	14.6
Rural	0.55	0.55	0.1	0.48	14.5
County has UNC campus	0.27	0.27	0.1	0.42	30.6
County has other 4yr campus	0.17	0.17	0.1	0.20	7.3
County has no 4yr campus	0.56	0.56	0.0	0.38	35.0
Cohort 2005-06	0.09	0.09	0.1	0.25	44.1
Cohort 2006-07	0.24	0.24	0.1	0.24	1.0
Cohort 2007-08	0.29	0.29	0.0	0.25	8.5
Cohort 2008-09	0.38	0.38	0.2	0.25	27.9
N	7241	399650	Mean = 0.3	399650	Mean = 15.7

Note. Standard deviations of continuous variables in parentheses. "ATT weighted" refers to propensity score weighted summary statistics, with weight set to 1 for ECHS students and PS/(1-PS) for non-ECHS students. Standardized difference calculated as: $(\bar{x}_{treat} - \bar{x}_{control})/\sqrt{\frac{s^2_{treat}-s^2_{control}}{2}}$ for continuous variables and $(\hat{p}_{treat} - \hat{p}_{control})/\sqrt{\frac{\hat{p}_{treat}(1-\hat{p}_{treat})+\hat{p}_{control}(1-\hat{p}_{control})}{2}}$ for categorical variables, where $\bar{x}$ refers to the mean, s^2 refers to variance, and $\hat{p}$ refer to the prevalence (mean), using the "pstest" command in Stata. Standardized differences greater than 10% indicate imbalance (Austin 2009; Stuart 2010; Leuven and Sianesi 2003).

Table 2

Effects of ECHSs on short-run math and science outcomes

Variable	Coeff.	SE	Treat margin	Comp margin	Marg diff
High school outcomes through Grade 12 (continuous)					
# College Courses Passed	8.276***	(0.633)		1.58	
# College Sci/Math Passed	1.266***	(0.159)		0.52	
# Any Sci/Math Passed	0.828***	(0.245)		7.34	
Overall HSGPA	0.002	(0.055)		2.55	
Sci/Math HSGPA	0.147**	(0.050)		2.24	
High school outcomes through Grade 12 (binary)					
Passed any college course	18.61***	(2.669)	0.878	0.425	0.453
Passed any college Sci/Math	6.427***	(1.266)	0.554	0.241	0.313
Degrees earned by Year 6 by field of study					
Any Degree	25.52***	(3.076)	0.289	0.020	0.269
Soc Sci/Lib Arts	53.000***	(7.330)	0.234	0.007	0.227
Non-health STEM/Psy.	15.780***	(3.085)	0.043	0.003	0.040
Healthcare	2.103***	(0.379)	0.005	0.002	0.003
Other	2.564***	(0.363)	0.021	0.008	0.013

Note. Results of categorical variables obtained from a propensity score (ATT) weighted logit regression, with coefficients measured as odds ratios. Results of continuous variables obtained from an ATT weighted OLS model. SE = standard error, clustered by 9th grade school. Margins for categorical outcomes indicate predicted probabilities of experiencing the outcome. Comparison margin for continuous outcomes refers to the comparison group mean. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted status, disability status, Limited English Proficiency status, whether there was a four-year public or private university in the student's 8th grade county, the student's 8th grade county urbanicity, and cohort year. High school outcomes sample restricted to students with observed data for all high school outcomes, N = 355,848. Postsecondary sample includes all students in the main analytic sample, N = 399,650.

Table 3

Effects of ECHS attendance on Bachelor's degree field of study by 10 years after high school entry

Major	OR	SE	ECHS Margin	Comp Margin	Marg Diff
STEM and STEM-related majors					
Nat Sci	1.531***	(0.123)	0.042	0.029	0.013
Math/CS	1.708***	(0.204)	0.016	0.010	0.006
Engineering	0.895	(0.100)	0.014	0.015	-0.001
Healthcare	0.838	(0.082)	0.018	0.021	-0.003
Psych	1.619***	(0.103)	0.033	0.021	0.012
Aggregated STEM categories					
STEM	1.414***	(0.110)	0.071	0.053	0.018
STEMM	1.216**	(0.089)	0.087	0.074	0.013
STEMM+Psych	1.338***	(0.083)	0.119	0.095	0.024
Other major categories					
Soc Sci	1.418***	(0.100)	0.031	0.022	0.009
Lib Arts	1.234***	(0.074)	0.058	0.048	0.010
Other	1.163*	(0.076)	0.115	0.102	0.013
Overall attainment					
Any BA	1.369***	(0.095)	0.295	0.248	0.047

Note. OR = odds ratio; SE = standard error, clustered by 9th grade school; STEMM = science, technology, engineering, mathematics, and medical (healthcare). Margins indicate predicted probabilities of experiencing the outcome. Results obtained from a propensity score (ATT) weighted logit regression. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted status, disability status, Limited English Proficiency status, whether there was a four-year public or private university in the student's 8th grade county, the student's 8th grade county urbanicity, and cohort year. N = 399,650.
* p < .05, ** p < .01, *** p < .001

Table 4

Sensitivity Analysis

Panel A: Natural Sciences

RR	1.00	1.25	1.50	1.75	2.00	2.25	2.50	2.75	3.00
1.0	1.508	1.508	1.508	1.508	1.508	1.508	1.508	1.508	1.508
1.1	1.508	1.481	1.462	1.449	1.439	1.432	1.426	1.421	1.417
1.2	1.508	1.458	1.424	1.400	1.382	1.368	1.357	1.348	1.340
1.3	1.508	1.438	1.392	1.359	1.334	1.315	1.299	1.287	1.276
1.4	1.508	1.422	1.364	1.323	1.293	1.269	1.249	1.234	1.221
1.5	1.508	1.407	1.340	1.293	1.257	1.229	1.206	1.188	1.173
1.6	1.508	1.395	1.320	1.266	1.225	1.194	1.169	1.148	1.131
1.7	1.508	1.384	1.301	1.242	1.198	1.163	1.135	1.113	1.094
1.8	1.508	1.374	1.285	1.221	1.173	1.136	1.106	1.081	1.061
1.9	1.508	1.365	1.270	1.202	1.151	1.111	1.079	1.053	1.032
2.0	1.508	1.357	1.257	1.185	1.131	1.089	1.056	1.028	1.005

Panel B: Engineering

RR	1.00	0.90	0.80	0.70	0.60	0.50	0.40	0.30	0.20
1.0	0.896	0.896	0.896	0.896	0.896	0.896	0.896	0.896	0.896
1.1	0.896	0.905	0.916	0.931	0.950	0.977	1.018	1.086	1.222
1.2	0.896	0.913	0.933	0.960	0.996	1.045	1.120	1.244	1.493
1.3	0.896	0.919	0.948	0.985	1.034	1.103	1.206	1.378	1.723
1.4	0.896	0.924	0.960	1.006	1.067	1.152	1.280	1.493	1.920
1.5	0.896	0.929	0.971	1.024	1.095	1.195	1.344	1.593	2.091
1.6	0.896	0.933	0.980	1.040	1.120	1.232	1.400	1.680	2.240
1.7	0.896	0.937	0.988	1.054	1.142	1.265	1.449	1.757	2.372
1.8	0.896	0.940	0.996	1.067	1.161	1.294	1.493	1.825	2.489
1.9	0.896	0.943	1.002	1.078	1.179	1.320	1.533	1.886	2.594
2.0	0.896	0.946	1.008	1.088	1.195	1.344	1.568	1.941	2.688

Note. Rows and columns refer to the risk ratio relationship between a potential confounder and treatment take-up and the confounder and the outcome (interchangeably). Cells indicate what the true risk ratio would be if a confounder with the strength indicated in the row and column existed. Estimated results obtained from the primary model estimates shown in Table 3 and converted to risk ratios using the formula described by Zhang & Yu (1998). Cell values identified using the bias formulas for sensitivity analysis described by VanderWeele & Ding (2017) and Mathur et al. (2018).

Table 5

Effect of ECHS attendance on Bachelor's degree field of study by 10 years after high school entry, selected student subgroups

	Any BA (1)	Nat Sci (2)	CS/Math (3)	Engineering (4)	Healthcare (5)	Psych (6)
Black/Hispanic						
ECHS (OR)	1.796***	2.008***	1.517	0.843	1.056	1.628***
SE	(0.210)	(0.349)	(0.367)	(0.276)	(0.156)	(0.162)
ECHS marg.	0.296	0.037	0.011	0.007	0.019	0.036
Comp marg.	0.210	0.019	0.007	0.008	0.018	0.023
Marg. Diff.	0.086	0.018	0.004	-0.001	0.001	0.013
N	148749	148749	148749	148749	148749	148749
White						
ECHS (OR)	1.137	1.274**	1.998***	0.902	0.700**	1.522***
SE	(0.077)	(0.104)	(0.229)	(0.106)	(0.088)	(0.151)
ECHS marg.	0.281	0.036	0.019	0.016	0.016	0.029
Comp marg.	0.262	0.029	0.010	0.017	0.023	0.019
Marg. Diff.	0.019	0.007	0.009	-0.001	-0.007	0.010
N	227229	227229	227229	227229	227229	227229
Male						
ECHS (OR)	1.390***	1.583***	2.059***	0.918	1.421	1.970***
SE	(0.122)	(0.183)	(0.246)	(0.110)	(0.305)	(0.300)
ECHS marg.	0.261	0.038	0.031	0.026	0.008	0.017
Comp marg.	0.215	0.025	0.016	0.028	0.005	0.009
Marg. Diff.	0.046	0.013	0.015	-0.002	0.003	0.008
N	203554	203554	203554	203554	203554	203554
Female						
ECHS (OR)	1.364***	1.497***	1.147	0.832	0.776*	1.563***
SE	(0.094)	(0.128)	(0.205)	(0.148)	(0.078)	(0.123)
ECHS marg.	0.316	0.044	0.007	0.006	0.025	0.043
Comp marg.	0.268	0.031	0.006	0.007	0.031	0.029
Marg. Diff.	0.048	0.013	0.001	-0.001	-0.006	0.014
N	196106	196106	196106	196106	196106	196106
ED						
ECHS (OR)	1.745***	1.674***	1.485	1.045	0.864	1.899***
SE	(0.147)	(0.232)	(0.389)	(0.235)	(0.154)	(0.230)
ECHS marg.	0.223	0.027	0.009	0.007	0.012	0.029
Comp marg.	0.154	0.016	0.006	0.006	0.014	0.016
Marg. Diff.	0.069	0.011	0.003	0.001	-0.002	0.013
N	176926	176926	176926	176926	176926	176926
Not ED						
ECHS (OR)	1.188*	1.472***	1.781***	0.870	0.819	1.453***
SE	(0.081)	(0.121)	(0.211)	(0.105)	(0.084)	(0.116)
ECHS marg.	0.364	0.055	0.023	0.020	0.023	0.037
Comp marg.	0.334	0.039	0.014	0.023	0.028	0.025
Marg. Diff.	0.030	0.016	0.009	-0.003	-0.005	0.012
N	222274	222274	222274	222274	222274	222274
Mid 1/3						

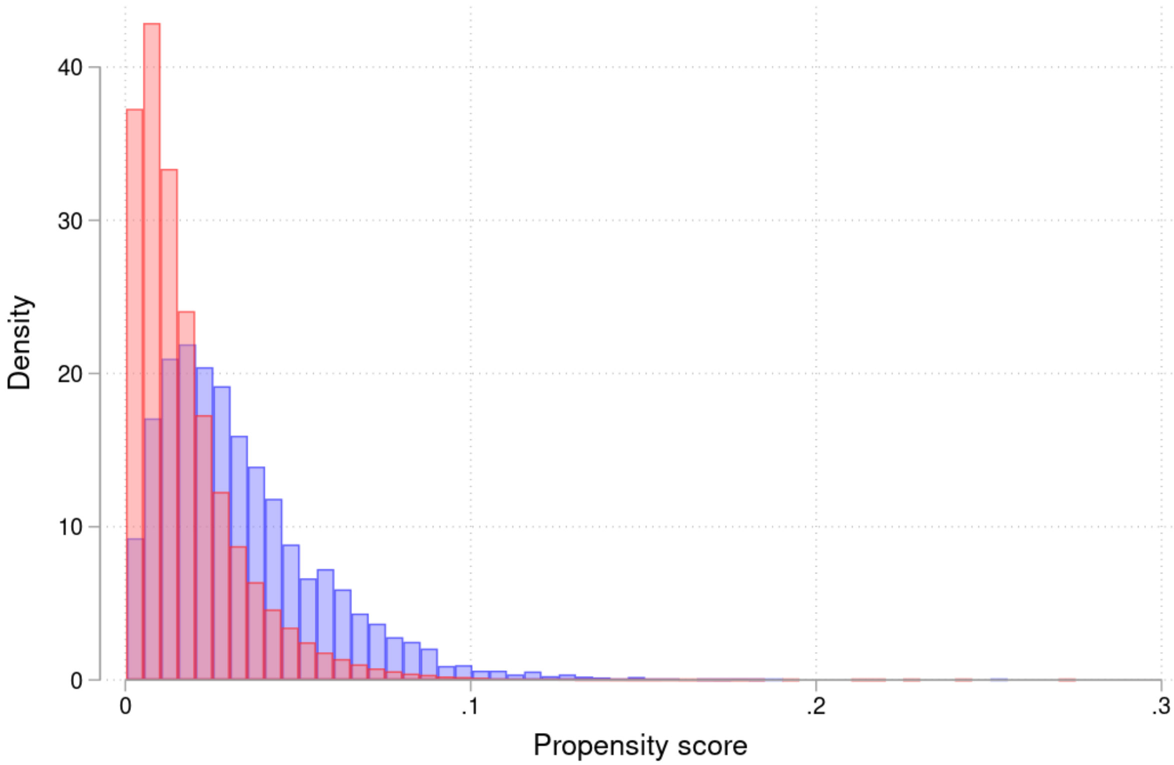
ECHS (OR)	1.594***	1.997***	1.703*	0.701	0.958	1.691***
SE	(0.169)	(0.408)	(0.433)	(0.243)	(0.167)	(0.158)
ECHS marg.	0.227	0.022	0.006	0.002	0.015	0.026
Comp marg.	0.164	0.011	0.003	0.004	0.015	0.016
Marg. Diff.	0.063	0.011	0.003	-0.002	0.000	0.010
N	130682	130682	130682	130682	130682	130682
Top 1/3						
ECHS (OR)	1.152*	1.367***	1.645***	0.897	0.735**	1.427***
SE	(0.072)	(0.102)	(0.211)	(0.106)	(0.085)	(0.107)
ECHS marg.	0.426	0.069	0.030	0.027	0.026	0.044
Comp marg.	0.397	0.052	0.019	0.030	0.035	0.032
Marg. Diff.	0.029	0.017	0.011	-0.003	-0.009	0.012
N	126758	126758	126758	126758	126758	126758
2-year partnered ECHS						
ECHS (OR)	1.271***	1.416***	1.545***	0.864	0.827	1.651***
SE	(0.068)	(0.099)	(0.190)	(0.272)	(0.086)	(0.121)
ECHS marg.	0.256	0.033	0.012	0.011	0.017	0.030
Comp marg.	0.223	0.024	0.008	0.013	0.020	0.018
Marg. Diff.	0.033	0.009	0.004	-0.002	-0.003	0.012
N	398501	398501	398501	398501	398501	398501
4-year partnered ECHS						
ECHS (OR)	1.971***	2.004***	2.267***	1.083	0.921	1.530***
SE	(0.345)	(0.362)	(0.430)	(0.212)	(0.211)	(0.107)
ECHS marg.	0.496	0.087	0.037	0.028	0.025	0.051
Comp marg.	0.372	0.048	0.018	0.026	0.027	0.035
Marg. Diff.	0.124	0.039	0.019	0.002	-0.002	0.016
N	158963	158963	158963	158963	158963	158963

Note. "ED" = "economically disadvantaged;" "Mid 1/3" and "Top 1/3" refer to student position in the middle school math achievement distribution; SE = standard error, clustered by 9th grade school. Margins indicate predicted probabilities of experiencing the outcome. Results obtained from a propensity score (ATT) weighted logit regression. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted, disability, and Limited English Proficiency status, and cohort year. Estimates obtained from models restricted to students in the focal subgroup. Comparison group for 2-year partnered ECHSs includes all non-ECHS students; comparison for 4-year partnered ECHSs includes only students whose 8th grade school was located in a county with a UNC campus.
* p < .05, ** p < .01, *** p < .001

Appendix A. Additional Figures

Appendix Figure A1

Distribution of propensity scores in treatment and comparison groups (common support)



Note. Blue bars indicate the distribution of estimated propensity scores for ECHS students; red bars indicate the distribution of estimated propensity scores for comparison students. Propensity scores obtained from a logit regression of treatment on student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted, disability, and Limited English Proficiency status, and cohort year. The propensity score is set equal to 1 for ECHS students and PS/(1-PS) for comparisons to generate an average treatment on the treated (ATT) weight.

Appendix B. Additional Tables

Appendix Table A1

Categorization of fields of study

Category	CIP Code and Description
STEM	4 – Architecture and Related Services
	10 – Communications Technologies/Technicians and Support Services
	11 – Computer and Information Sciences and Support Services
	14 – Engineering
	15 – Engineering Technologies/Technicians
	26 – Biological and Biomedical Sciences
	27 – Mathematics and Statistics
	40 – Physical Sciences
	41 – Science Technologies/Technicians
Healthcare (Medical)	51 – Health Professions and Related Clinical Sciences
Psychology	42 – Psychology
Social Sciences	45 – Social Sciences
Liberal Arts	5 – Area, Ethnic, Cultural, and Gender Studies
	9.01 – Communication and Media Studies
	16 – Foreign Languages, Literatures, and Linguistics
	23 – English Language and Literature/Letters
	24 – Liberal Arts and Sciences, General Studies, and Humanities
	38 – Philosophy and Religious Studies
	50 – Visual and Performing Arts
	54 – History
Other Applied	1 – Agriculture, Agriculture Operations, and Related Sciences
	3 – Natural Resources and Conservation
	9.02-9.99 – Other Communication, Journalism, and Related Programs
	12 – Personal and Culinary Services
	13 – Education
	19 – Family and Consumer Sciences/Human Sciences
	22 – Legal Professions and Studies
	25 – Library Science
	30 – Multidisciplinary Studies
	31 – Parks, Recreation, Leisure, and Fitness Studies
	36 – Leisure and Recreational Activities
	39 – Theology and Religious Vocations
	43 – Security and Protective Services
	44 – Public Administration and Social Service Professions
	46 – Construction Trades
	47 – Mechanic and Repair Technologies/Technicians
	48 – Precision Production
	49 – Transportation and Materials Moving
	52 – Business Management, Marketing, and Related Support Services

Note. This list includes all CIP codes that appeared in the University of North Carolina system, the North Carolina Community College system, or the National Student Clearinghouse data for the North Carolina student sample

Appendix Table A2

Comparison of estimates from PSW and unweighted regression models

	PSW ATT (1)		PSW ATE (2)		Regression (3)	
	OR	SE	OR	SE	OR	SE
STEM and STEM-related majors						
Nat Sci	1.531***	(0.123)	1.688***	(0.192)	1.595***	(0.166)
Math/CS	1.708***	(0.204)	1.783***	(0.273)	1.793***	(0.246)
Engineering	0.895	(0.100)	0.853	(0.105)	0.931	(0.110)
Healthcare	0.838	(0.082)	0.854	(0.129)	0.883	(0.093)
Psych	1.619***	(0.103)	1.485***	(0.099)	1.732***	(0.128)
Aggregated STEM categories						
STEM	1.414***	(0.110)	1.481***	(0.151)	1.478***	(0.142)
STEMM	1.216**	(0.089)	1.258*	(0.119)	1.273**	(0.110)
STEMM+Psych	1.338***	(0.083)	1.334***	(0.112)	1.415***	(0.103)
Other major categories						
Lib Arts	1.418***	(0.100)	1.150	(0.909)	1.306***	(0.094)
Soc Sci	1.234***	(0.074)	1.331**	(0.161)	1.508***	(0.108)
Other	1.163*	(0.076)	1.080	(0.100)	1.224**	(0.096)
Overall attainment						
Any BA	1.369***	(0.095)	1.276*	(0.132)	1.452***	(0.117)

Note. OR = odds ratio; SE = standard error, clustered by 9th grade school; STEMM = science, technology, engineering, mathematics, and medical (healthcare). Model 1 results obtained from a propensity score (ATT) weighted logit regression. Model 2 results obtained from a propensity score (ATE) weighted logit regression. Model 3 obtained from a logit regression with no propensity score adjustment. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted status, disability status, Limited English Proficiency status, whether there was a four-year public or private university in the student's 8th grade county, the student's 8th grade county urbanicity, and cohort year. N = 399,650.
* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix Table A3

Effects of ECHS attendance on degree field of study of Bachelor's degree earners

Major	OR	SE	ECHS Margin	Comp Margin	Marg Diff
STEM and STEM-related majors					
Nat Sci	1.319**	(0.107)	0.135	0.107	0.028
Math/CS	1.446**	(0.159)	0.054	0.039	0.015
Engineering	0.776*	(0.086)	0.044	0.055	-0.011
Healthcare	0.676***	(0.060)	0.059	0.085	-0.026
Psych	1.321***	(0.075)	0.111	0.087	0.024
Aggregated STEM categories					
STEM	1.224**	(0.089)	0.230	0.200	0.030
STEMM	1.011	(0.068)	0.284	0.282	0.002
STEMM+Psych	1.119*	(0.060)	0.393	0.367	0.026
Other major categories					
Soc Sci	1.177*	(0.082)	0.104	0.090	0.014
Lib Arts	1.015	(0.066)	0.191	0.189	0.002
Other	0.849**	(0.043)	0.388	0.427	-0.039

Note. OR = odds ratio; SE = standard error, clustered by 9th grade school; STEMM = science, technology, engineering, mathematics, and medical (healthcare). Margins indicate predicted probabilities of experiencing the outcome. Results obtained from a propensity score (ATT) weighted logit regression with sample restricted to students who earned a Bachelor's degree. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted status, disability status, Limited English Proficiency status, whether there was a four-year public or private university in the student's 8th grade county, the student's 8th grade county urbanicity, and cohort year. N = 86,054.
* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix Table A4

Effects of ECHS attendance on field of study of highest degree earned (Associate's or Bachelor's) by Year 10

Major	OR	SE	ECHS Marg	Comp Marg	Marg Diff
Any degree	2.152***	(0.129)	0.473	0.330	0.143
Soc Sci/Lib Arts	5.162***	(0.519)	0.287	0.082	0.205
Non-health STEM/Psy.	2.045***	(0.130)	0.126	0.070	0.056
Healthcare	0.901	(0.056)	0.040	0.044	-0.004
Other	1.153**	(0.062)	0.146	0.130	0.016

Note. OR = odds ratio; SE = standard error, clustered by 9th grade school; Margins indicate predicted probabilities of experiencing the outcome. Outcomes indicate the field of study of students' highest degree earned by Year 10 – for students who earned an Associate's and a Bachelor's, the Bachelor's field of study is used. Results obtained from a propensity score (ATT) weighted logit regression. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted status, disability status, Limited English Proficiency status, whether there was a four-year public or private university in the student's 8th grade county, the student's 8th grade county urbanicity, and cohort year. N = 399,650.
* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix Table A5

Robustness of estimates of ECHS attendance on Bachelor's degree attainment by 10 years after high school entry

	Full Sample (1)		2009 Sample, No Sci Control (2)		2009 Sample, w/Sci Control (3)		% change (2 vs 3)
Major	OR	SE	OR	SE	OR	SE	
STEM and STEM-related majors							
Nat Sci	1.531***	(0.123)	1.484**	(0.192)	1.438**	(0.188)	-9.5%
Math/CS	1.708***	(0.204)	1.413	(0.251)	1.358	(0.242)	-13.7%
Engineering	0.895	(0.100)	0.885	(0.164)	0.866	(0.160)	-16.5%
Healthcare	0.838	(0.082)	0.775	(0.110)	0.776	(0.111)	+0.4%
Psych	1.619***	(0.103)	1.720***	(0.200)	1.721***	(0.200)	+0.0%
Aggregated STEM categories							
STEM	1.414***	(0.110)	1.337*	(0.152)	1.287*	(0.148)	-14.8%
STEMM	1.216**	(0.089)	1.151	(0.122)	1.120	(0.119)	-20.5%
STEMM + Psy.	1.338***	(0.083)	1.297**	(0.115)	1.268**	(0.113)	-9.8%
Other Major Categories							
Lib Arts	1.418***	(0.100)	1.234*	(0.113)	1.221*	(0.112)	-4.6%
Soc Sci	1.234***	(0.074)	1.520***	(0.170)	1.511***	(0.168)	-1.7%
Other	1.163*	(0.076)	1.238**	(0.086)	1.276***	(0.088)	+16.0%
Overall Attainment							
Any BA	1.369***	(0.095)	1.384***	(0.116)	1.385***	(0.115)	+0.0%

Note. Results, measured as odds ratios, indicate the effect of attending an ECHS in 9th grade on earning a Bachelor's degree by field of study by 10 years after high school entry. Results obtained from a propensity score (ATT) weighted logit regression. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, and indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted status, disability status, Limited English Proficiency status, whether there was a four-year public or private university in the student's 8th grade county, the student's 8th grade county urbanicity, and cohort year. Sample includes students who entered 9th grade in a North Carolina public high school between 2005-06 and 2008-09. Margins, obtained using the "mimrgns" Stata command, indicate predicted probabilities of earning a degree by field of study. Standard errors clustered by 9th grade school. Full Sample N = 399650, 2009 Sample N = 95572.
* p < .05, ** p < .01, *** p < .001

Appendix Table A6

Key balance statistics for subsamples

	Mean Std Diff	Max Std Diff	N Treat
Black/Hispanic	0.4%	4.0%	2585
White	0.3%	1.9%	4070
Male	0.3%	2.7%	2896
Female	0.3%	3.5%	4345
Econ. Disadvantaged	0.3%	3.3%	3651
Not Econ. Disadvantaged	0.3%	2.7%	3590
Mid 1/3 baseline math	0.2%	2.5%	2801
Top 1/3 baseline math	0.2%	1.5%	3091
2-yr partnered ECHS	0.3%	2.4%	6092
4-yr partnered ECHS	0.4%	5.3%	1146
Bachelor's earners	0.3%	2.1%	2088
2009 cohort, w/science variable	0.3%	2.4%	2708
2009 cohort, w/o science variable	0.3%	1.9%	2708

Note. Results present key balance statistics for weighted subgroups. "Mean Std Diff" refers to the mean absolute standardized difference between ECHS and weighted comparison students over all covariates in the model; "Max Std Diff" refers to the highest absolute standardized difference of any covariate in the model. Standardized difference calculated as: $(\bar{x}_{treat} - \bar{x}_{control}) / \sqrt{\frac{s^2_{treat} - s^2_{control}}{2}}$ for continuous variables and $(\hat{p}_{treat} - \hat{p}_{control}) / \sqrt{\frac{\hat{p}_{treat}(1-\hat{p}_{treat}) + \hat{p}_{control}(1-\hat{p}_{control})}{2}}$ for categorical variables, where $\bar{x}$ refers to the mean, s^2 refers to variance, and $\hat{p}$ refer to the prevalence (mean), using the "pstest" command in Stata. Standardized differences greater than 10% indicate imbalance (Austin 2009; Stuart 2010; Leuven and Sianesi 2003).

Appendix Table A7

Effects of ECHS attendance on STEM Bachelor's degree attainment by subgroup, alternative definitions of STEM

Subgroup	OR	SE	ECHS Margin	Comp Margin	Marg Diff	N
Traditional STEM						
Black/Hispanic	1.634**	(0.286)	0.054	0.035	0.019	148,749
White	1.304***	(0.086)	0.071	0.057	0.014	227,229
Male	1.427***	(0.128)	0.091	0.069	0.022	203,544
Female	1.373***	(0.114)	0.058	0.044	0.014	196,106
ED	1.533***	(0.179)	0.042	0.029	0.013	176,926
Not ED	1.366***	(0.107)	0.096	0.075	0.021	222,724
Mid 1/3	1.700**	(0.300)	0.030	0.018	0.012	130,682
Top 1/3	1.306***	(0.090)	0.124	0.100	0.024	126,758
2-yr ECHS	1.293***	(0.080)	0.056	0.045	0.011	398,501
4-yr ECHS	1.922***	(0.347)	0.148	0.091	0.057	158,963
STEM + Medical (STEMM)						
Black/Hispanic	1.418*	(0.222)	0.070	0.052	0.018	148,749
White	1.098	(0.072)	0.086	0.080	0.006	227,229
Male	1.424***	(0.130)	0.097	0.074	0.023	203,544
Female	1.079	(0.080)	0.080	0.075	0.005	196,106
ED	1.304*	(0.154)	0.054	0.043	0.011	176,926
Not ED	1.175*	(0.081)	0.117	0.103	0.014	222,724
Mid 1/3	1.332	(0.207)	0.044	0.034	0.010	130,682
Top 1/3	1.129	(0.071)	0.147	0.134	0.013	126,758
2-yr ECHS	1.131*	(0.065)	0.072	0.065	0.007	398,501
4-yr ECHS	1.603*	(0.299)	0.166	0.117	0.049	158,963
STEMM + Psych						
Black/Hispanic	1.513**	(0.184)	0.105	0.075	0.030	148,749
White	1.206**	(0.077)	0.114	0.098	0.016	227,229
Male	1.512***	(0.127)	0.113	0.082	0.031	203,544
Female	1.241***	(0.081)	0.121	0.103	0.018	196,106
ED	1.468***	(0.151)	0.081	0.059	0.022	176,926
Not ED	1.269***	(0.073)	0.153	0.128	0.025	222,724
Mid 1/3	1.469***	(0.167)	0.069	0.049	0.020	130,682
Top 1/3	1.215***	(0.066)	0.190	0.164	0.026	126,758
2-yr ECHS	1.269***	(0.065)	0.101	0.083	0.018	398,501
4-yr ECHS	1.653**	(0.269)	0.213	0.150	0.063	158,963

Note. "ED" = "economically disadvantaged;" "Mid 1/3" and "Top 1/3" refer to student position in the middle school math achievement distribution; SE = standard error, clustered by 9th grade school. Margins indicate predicted probabilities of experiencing the outcome. Results obtained from a propensity score (ATT) weighted logit regression. Covariates include student race/ethnicity, sex, economic disadvantage, parent education, average middle school math and reading test scores and absences, indicators of having taken Algebra I by 8th grade, switching schools in middle school, academically or intellectually gifted, disability, and Limited English Proficiency status, and cohort year. Estimates obtained from models restricted to students in the focal subgroup. Comparison group for 2-year partnered ECHSs includes all non-ECHS students; comparison for 4-year partnered ECHSs includes only students whose 8th grade school was located in a county with a UNC campus. * $p < .05$, ** $p < .01$, *** $p < .001$

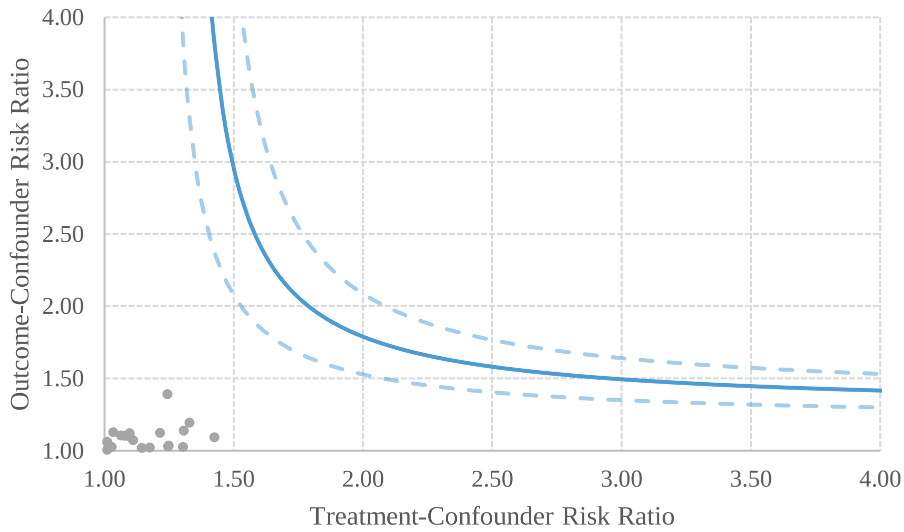
Appendix C. Alternative Sensitivity Analysis

This appendix displays an alternative version of the sensitivity analysis shown in Section VI.d. in which I aim to directly assess whether a confounder could explain the shifts observed within STEM. To do so, I ran an auxiliary model restricted to students who earned a degree in "STEMM" and estimated the effect of ECHSs on having majored in the natural sciences, computer science, or math instead of engineering or healthcare, which produces a formal estimate of the shift within STEMM. I estimate an 83 percent increase in the odds (or a risk ratio of 1.28) that students who earned a degree in STEMM did so in the natural sciences, math, or computer science, similar to the difference in the average odds ratios from Table 3 on natural sciences and math/computer science compared to engineering and healthcare.

Figure C1 plots the sensitivity analysis. The solid curved line indicates risk ratio values that a confounder would need to have with treatment take-up (RR_{EU}) and the outcome (RR_{UD}) to nullify this estimate, while the dashed lines indicate values that would nullify the estimate at the lower or upper bounds of the 95% confidence interval. The value where RR_{UD} and RR_{EU} are the same is the "e-value" (VanderWeele and Ding 2017; Mathur et al. 2018). The e-value in this scenario is 1.89. This means that a confounder that approximately doubled the likelihood that a student earned a degree in the natural sciences, math, or computer science instead of engineering or healthcare, net of observed covariates, would also need to nearly double the likelihood that a student entered an ECHS to nullify the observed shift in STEM majors among ECHS students.

For context, I also plot the relationships of all observed covariates with treatment take-up and this outcome in Figure 1. The strongest observed covariates increase the likelihood that a student majored in natural science, math, or computer science rather than engineering or healthcare by only about 50 percent. Thus, a confounder would need to be much stronger than observed variables and impact treatment take-up to nullify this pattern of results.

Appendix Figure C1. *Sensitivity Analysis*



Note. Chart shows results of a VanderWeele & Ding (2017) sensitivity analysis. The solid blue line indicates risk ratio relationships that an unobserved confounder would need to have with treatment take-up (X-axis) and the outcome (Y-axis) to nullify results (X-Y points above this line would nullify results). Dashed lines indicate values that would nullify estimates at the lower and upper bounds. Outcome defined as having majored in the natural sciences, math, or computer science as compared to having majored in engineering or healthcare for students who completed a Bachelor's degree in one of these fields, obtained from an auxiliary model. Scatter points indicate risk ratio relationships of observed covariates with treatment take-up (from the primary model) and the outcome (from the auxiliary model). Risk ratio relationships for continuous covariates were obtained from an auxiliary model where these variables were trichotomized to be able to generate a risk ratio. Odds ratios were converted to risk ratios using the formula $RR = \frac{OR}{(1-P_{ref})+(P_{ref}*OR)}$, where P_{ref} refers to the probability of the outcome in the comparison group (Zhang and Yu 1998). Covariates with risk ratio values with treatment or the outcome below 1 were inverted to plot all covariates in the same quadrant.