Malleable minds: The effects of STEM v. humanities-focused curricula

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Abstract

We examine the impact of assignment to STEM v. humanities-focused curricula in Romania's high school system. We apply a regression discontinuity design to administrative and survey data to estimate effects on educational pathways, career plans, and non-cognitive outcomes. An overarching theme of our findings is the malleability of students to what they study. Assignment to STEM increases STEM college enrollment by 23 pp and STEM career intentions by 17 pp, with corresponding negative effects on humanities-related enrollment and career plans. Exploring mechanisms, we find that STEM assignment changes students' self-perceived academic abilities and their preferences over academic subjects and job tasks. We find less evidence for stories related to sunk costs, peer and teacher influences, or beliefs about earnings and work conditions. Importantly, STEM assignment involves a risk: it improves wellbeing, high school satisfaction, and career prospects on average, but reduces performance on a high school exit exam, leading to lower college enrollment and retrospective satisfaction among low-achieving students. Similarly, it makes female students report negative experiences with college professors and peers. A final finding is that male students become more conservative. We provide suggestive explanations for our results on wellbeing and political preferences by measuring effects on time use, friendships, and expectations.

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1 Introduction

Modern education systems allow for curricular specialization and choice. While it is almost universal that college students choose a major, specialization is also a feature of many high school systems around the world. A central question in education is understanding how exposure to a curricular focus affects educational, labor market, and non-cognitive outcomes.

This broad question is often studied with respect to the costs and benefits of STEM versus humanities education. The literature in economics usually focuses on the (positive) labor market returns to a STEM degree (Cortes, Goodman, and Nomi 2015; Darolia et al. 2020; Goodman 2019; Cohodes, Ho, and Robles 2022; Liu, Conrad, and Blazar 2024; Joensen and Nielsen 2009, 2016; De Philippis 2021; Dahl, Rooth, and Stenberg 2023a). This has led to an interest in increasing STEM enrollments, both in general and among subgroups (e.g., women) less likely to pursue STEM fields.

In this paper, we examine the impact of exposure to a STEM v. humanities/social studies (henceforth HSS) curriculum. In Romania, a centralized admission system allocates students to high school tracks delivering specialized curricula, which allows us to implement a regression discontinuity design that takes advantage of the cutoff scores required to attend different tracks. In other words, we compare otherwise very similar students assigned to STEM v. HSS.[1] We apply this design to administrative and large-scale survey data to provide a comprehensive analysis of high school performance, college enrollment, career plans, high school/college satisfaction, wellbeing, time use, and beliefs and preferences.

Malleability of students in response to curricular exposure in high school is an overarching theme of our findings. We find, first, that exposure to curricula has large and persistent effects in shaping student educational, labor-market and non-cognitive outcomes, and, second, that this exposure has substantial effects on preferences and beliefs. While there has been considerable focus on early childhood interventions (Heckman 2006; Heckman et al. 2010; Del Boca, Flinn, and Wiswall 2014), our results suggest that teenagers retain enough plasticity for schooling interventions to be remarkably effective, consistent with a large body of work in neuroscience and developmental psychology (e.g., Galván (2017)).

Our contribution, in addition to presenting a comprehensive view of students' response to a STEM high school curriculum, is to investigate tradeoffs from, and mechanisms underlying, these impacts. Assignment to a STEM curriculum greatly increases high school graduation from a STEM track, STEM college enrollment, and STEM career intentions, with corresponding negative effects on humanities. However, we find a risk-reward tradeoff from STEM for low baseline performance students, who stand to gain from remunerative STEM careers but who are less likely to graduate from high school and to be enrolled in college. Another potential tradeoff from

1. Our approach is in the spirit of those used in Pop-Eleches and Urquiola (2013) and Ainsworth et al. (2023).

STEM for which we find some evidence has been highlighted by Nussbaum (2010), who argues for the importance of liberal arts education in fostering democratic citizenship, critical thinking, and empathy—as compared to education approaches that prioritize economic productivity. Consistent with this, we find that STEM assignment leads male students to adopt more traditional and conservative social values.

Disentangling the mechanisms underlying these results is important not only for designing policies to increase participation in a field of study, but also for understanding impacts on welfare. For example, early exposure to STEM could change student preferences over college academic subjects and career attributes. Alternatively, one can imagine a world where choice of college curriculum or career depends on fixed self-perceived aptitudes or sunk costs (e.g., where students feel they have invested too much to leave STEM). We are able to investigate both of these, and our results suggest that preferences are, in fact, malleable, although we cannot fully rule out other mechanisms.

Romanian high schools are divided into self-contained *tracks* with highly differentiated curricula. Middle school students apply to tracks by filling out a preference ranking over tracks. They are allocated to tracks via a centralized serial dictatorship mechanism that prioritizes the choices of students with high middle school grades ("transition scores"), computed as averages of their GPAs and scores on a national high school admission exam. This allocation mechanism generates minimum transition score cutoffs for oversubscribed tracks, which we exploit in a regression discontinuity framework.

We focus on students whose transition scores are on either side of cutoffs where they would be assigned to a track with a different curriculum if their transition score were above or below the cutoff. Some students' transition scores are close to cutoffs where scoring above leads to being allocated to a track with a STEM curriculum and scoring below leads to landing in HSS. Conversely, students' transition scores can be close to cutoffs where scoring above leads to HSS and below leads to STEM. By averaging these two effects, we can estimate the causal effect of being assigned to STEM. The treatment effects we capture result from exposure to a different curriculum, which means being taught different subjects, but potentially also different peers and teachers. By averaging out the cases where STEM tracks are more selective with cases where STEM tracks are less selective, we control for peer achievement levels or track selectivity—although other peer characteristics (e.g., relative ability in STEM versus HSS, interests, and gender composition) could still play a role. We return to a discussion of the decomposition of the treatment effect below.

To measure the effects of curriculum exposure across a broad range of outcomes and across time, we use administrative data on four cohorts of students representing the universe of students in 16 of the 41 Romanian counties. These include admission records (middle school GPAs, admission exam scores, ranked preferences over high school tracks, and track allocations), high

school enrollment records (dropout, transfers, grade repetitions), and high school graduation records (with scores on the Baccalaureate—a national end-of-high school exam). These allow us to measure effects on high school enrollment and performance. We complement these data with three follow-up surveys tracking the cohort admitted to high school in 2019 in their transition from high school to college (or the labor market), through which we measure college enrollment, career plans, high school and college satisfaction, wellbeing, time use, and beliefs and preferences.

Our findings are as follows. We first show that being assigned to a STEM track causes students to pursue STEM in college and to plan for STEM careers at much higher rates. The effects are strikingly large: assignment to a STEM high school track does not affect college attendance, but increases enrollment into STEM fields by 23 percentage points (pp), while decreasing enrollment into HSS, law, or social science majors.

There is remarkably little heterogeneity in these effects; for example by: i) preferences for the STEM track at the cutoff when applying for high school, ii) relative ability in mathematics v. languages at baseline, and iii) gender. This suggests that match effects are of second order compared to exposure to different curricula. It also suggests that interventions of this type could boost STEM enrollment for most groups.

However, there are risk-reward tradeoffs associated with different curricula. While STEM may lead to higher returns, low-achieving students assigned to STEM: i) do worse on the end-of-high-school exit exam, passing it at lower rates, ii) are less likely to attend college, iii) are less likely to attend a prestigious college, iv) are less likely to pass their first-year winter exams, and v) become more interested in business careers. While these results are within the Romanian context, where the high school graduation exam is curriculum-specific, they could arise in other contexts. Indeed, U.S. college GPAs tend to be much lower in STEM than in humanities.[2] Policymakers should thus be aware that incentivizing low-achievers to pursue STEM may prove a risky proposition.

The main mechanisms to emerge from our results inducing these changes are self-efficacy and preferences for subjects. We find that STEM assignment leads students to think they are better at STEM subjects (by 1.3 standard deviations), and to like STEM subjects more (1.4 sd). These effects persist at least one year after high school graduation. Again, this is the case for all students, regardless of gender, initial interests, and initial relative ability across subjects. Students report that abilities and interests (together with labor market prospects) are the most important factors in their decision over college majors. Conversely, students report that the decisions of peers and sunk costs rank low on their list of reasons for choosing college majors and careers. Thus, beliefs and preferences channels likely explain the effects on college and career outcomes.

Despite finding evidence that STEM is a more challenging high school subject, being assigned

2. See, for example, Gorelick (2023) and Rojstaczer and Healy (2023).

to STEM has little effect on how students evaluate their experience at the end of high school, except for making them like their peers more. This effect slightly diminishes over time; we document a decline in liking the high school curriculum in the year after high school versus at the end of high school, particularly for female students and low-achieving students. It also makes low-achieving students less satisfied with their high school application choices one year after high school. Overall, however, STEM students do not experience any regret over their high school applications.

On the other hand, being assigned to STEM in high school makes students like college less, an effect that is stronger among female students. The latter report lower satisfaction with college peers and instructors. It also makes students like college less than high school. However, it increases the extent to which students think they are well-prepared for college. In addition, it either does not affect students' satisfaction with their college application choices, or it makes students more satisfied with these choices. This is consistent with higher expected returns from a STEM career, but also with more favorable preferences over STEM careers and subjects.

Being assigned to STEM increases wellbeing at the end of high school, particularly for females, despite the more difficult curriculum. We also document changes in time use. STEM students spend 15 more minutes per day (1.6 s.d.) doing homework. It also makes students spend less time on social media (particularly for females), and less time reading (particularly for males). In addition, being assigned to STEM makes students have more male friends and fewer female friends (particularly for males). This could mechanically arise because their STEM peers are 15 p.p. more likely to be male. Additionally, it leads males to hold more conservative or traditionalist viewpoints and right-wing economic and social preferences.

Finally, to better understand which elements of assignment have the greatest impact, we explore whether effects are due to the difference in curriculum between STEM and HSS or due to differences in peer composition. Our empirical strategy makes being assigned to STEM orthogonal to average peer quality, but not to peers' relative academic strength or share female. We provide evidence against the peer explanation: i) students do not report that peers are a major factor in their college decisions; ii) we find no effect of average peer quality when examining within-curriculum cutoffs; and iii) in a cutoff-by-cutoff analysis we find that the magnitude of treatment effects on outcomes of interest is only loosely related to the magnitude of effects on peer attributes. Nonetheless, we acknowledge that we cannot fully rule out that peers play a role.[3]

3. We might also expect peer channels to work against our results. For instance, female students would be expected to have a worse STEM experience due to a lower share of female peers. However, female students in our sample experience treatments effects of similar magnitudes to the male students.

2 Literature Review

An extensive literature examines the causal effect of field of study on labor market outcomes, such as earnings. It considers this question at both the high school and college level, and in multiple countries including the U.S. (Goodman 2019; Bleemer and Mehta 2022; Andrews et al. 2022), the U.K. (Walker and Zhu 2011), Chile (Hastings, Neilson, and Zimmerman 2013), Norway (Kirkeboen, Leuven, and Mogstad 2016), and Sweden (Dahl, Rooth, and Stenberg 2023b). Altonji, Blom, and Meghir (2012), Altonji, Arcidiacono, and Maurel (2015), and Patnaik, Wiswall, and Zafar (2020) provide useful reviews and generally find that there are higher labor market returns to subjects that are more mathematical in nature, such as STEM.

The literature examining how to increase STEM enrollments is less extensive, and has typically focused on the effect of high school course offerings on college enrollment (Cortes, Goodman, and Nomi 2015; Darolia et al. 2020; Liu, Conrad, and Blazar 2024; Joensen and Nielsen 2009; De Philippis 2023). A limitation of these studies is that to fundamentally shift their skills and preferences, students have to voluntarily take numerous further courses. Stronger interventions, such as STEM summer programs, have been shown to increase college degree completion for underrepresented youth, but it is unclear how costly or scalable these are (Cohodes, Ho, and Robles 2022). The present study contributes to this literature by showing that quasi-random assignment to a STEM curriculum—an easy to scale (indeed already offered at scale) intervention—greatly increases STEM college enrollment and STEM career plans. Our findings also suggest that this is the case in equal measure for girls, boys, and high- and low-achievers.

Much of the literature has focused on the roles of pecuniary and non-pecuniary returns to education, risk aversion, and patience in shaping major choices, with residual differences between groups often attributed to differences in preferences; see for example Patnaik, Wiswall, and Zafar (2020) for a review. In contrast, Zafar (2013) shows that enjoyment of coursework and parental approval are more important than other factors in determining major choice. The literature is also silent on how malleable these factors are. We demonstrate that when it comes to curricular choice, "eating creates appetite": exposure to different curricula increases i) how enjoyable students find coursework in the field they are exposed to, ii) how enjoyable they find tasks related to occupations in that field, and iii) their self-confidence in subjects related to that field. These factors respond to curricular exposure and are the main reasons students cite for their subsequent major choices, far outweighing parental approval, earnings considerations, or switching costs.

Finally, there is limited research on the causal effects of field of study on non-labor market outcomes, such as well being, social ties, non-cognitive skills, or preferences over social and economic issues.[4] This omission is important for three reasons. First, as suggested, research

4. A notable exception is Paredes, Paserman, and Pino (2023), which suggests that studying economics causes students to have greater gender biases.

finds that households weigh attributes beyond labor market returns when making schooling decisions (Wiswall and Zafar 2015; Delavande and Zafar 2019; Ainsworth et al. 2023; Beuermann et al. 2023). Thus, understanding the effects of field of study on these other outcomes can help households make informed choices. Second, research shows that the quantity and quality of education can impact these other outcomes.[5] Thus, it is plausible that there may be an impact of field of study may as well. Third, arguments in favor of less mathematical subjects often center on their effects on non-labor market outcomes. For instance, Nussbaum (2010) claims that the humanities play a role in creating civic-minded citizens and in facilitating democracy. Thus, it is important to bring causal evidence to this discussion.[6] In our context, we find that curricular exposure affects time use, increases conservatism in male students, and increases well being.

3 Setting and data

We begin by describing the Romanian high school system, and then discuss the administrative we use and our surveys.

3.1 Setting

3.1.1 High School System

Romanian students begin to experience significant curricular differentiation during high school (grades 9 to 12). Within high schools, students are assigned to different tracks, which are self-contained units ("schools-within-a-school") with a specific curricular orientation, emphasizing different subjects. Tracks broadly fall into three categories: STEM, humanities/social studies (HSS) and technical/vocational. In this paper, we focus mainly on STEM and HSS. One reason for this is that technical tracks cover many different types of subject areas — many of them akin to STEM — but cater mainly to students who do not want to pursue higher education. Tracks are highly specialized, exposing students to very different courses. We show the number of hours of instruction across different subjects in Table 1. STEM students are exposed to 6 additional hours of instruction in science and math compared to HSS students, who instead are taught more language and humanities courses. Lastly, tracks are standardized at the national level; there is little variation in the course offerings across tracks within the same curricular focus and students have relatively little flexibility in designing their own curriculum.

5. As examples, see Lochner and Moretti (2004), Jackson (2018), Billings, Deming, and Ross (2019), Jackson et al. (2020), and Rose, Schellenberg, and Shem-Tov (2022) for effects on non-cognitive skills and crime, Rao (2019), Billings, Chyn, and Haggag (2021), and Apfeld et al. (2022b, 2023) for effects on political preferences, and Milligan, Moretti, and Oreopoulos (2004), Cohodes and Feigenbaum (2021), and Apfeld et al. (2022a) for effects on political participation.

6. There is some evidence on the effects of civics-oriented curricular changes. For instance, Clots-Figueras and Masella (2013) find that introducing Catalan language instruction in Catalonian schools caused students to more strongly identify as Catalonian. Also, Cantoni et al. (2017) find that a civics-oriented curriculum in Chinese high schools caused students to become more favorable toward the Chinese government. However, as far as we know, there is no causal research on the civic effects of field of study.

Table 1: Weekly Hours of Instruction Across Tracks

	STEM	HSS
Science and Math	14	8
Languages and Humanities	12	17
Other	3	4
Total	29	29

Note: Weekly hours of instruction across different subjects for STEM and HSS tracks.

Romanian high school students can choose which track they wish to attend. At the end of grade 8, students apply for high school tracks. They begin by writing a national high school admission exam[7] and receive a *transition score*: the average of their grade 5-8 GPA and their score on the admission exam. After receiving their transition scores and observing the number of seats available in each track, students submit a *preference ranking* over high school tracks they wish to attend. This listing can be long.[8]

Students are assigned to tracks via a centralized *serial dictatorship* mechanism that prioritizes the choices of high-scoring students. Specifically, the mechanism assigns the top-scoring student to her most preferred high school-track. Then it does the same for the second, and then for the third. Eventually, the mechanism reaches a student whose most-preferred option is full; it assigns him to his second-most preferred if available, and so on. As tracks fill with top-scorers, fewer and fewer seats remain for the lower-scoring students. Thus, oversubscribed tracks develop a *minimum transition score* cutoff required for admission. Our empirical approach exploits these cutoffs in a regression discontinuity framework.

This mechanism creates two additional analytically useful features. First, it induces sorting by ability. This arises because higher-scoring students, who have priority in choosing tracks, tend to cluster into the tracks that are typically selective, in prestigious high schools. Second, each track can be characterized by cutoff or minimum transition score — the minimum application score required to get into it. As detailed below, we rely on those cutoffs to implement a regression discontinuity design.

Students can apply to any high school track, but once the mechanism assigns them to a track, it is relatively difficult for them to transfer. Specifically, students can transfer to a different high school track, but only if their transition score is higher than the cutoff score for that track and if the target track is not beyond capacity.[9] Transferring to a track with a different curricular focus

7. The admission exam takes place over several days and has several components, including Romanian and mathematics.

8. Specifically, the list may contain up to 280 entries, a much higher number than the vast majority of students are likely to use.

9. Tracks typically have numbers of seats that are multiples of 28, which is the standard class size. Students

is more difficult after the first year of high school, as it also requires that students pass exams specific to the curriculum to which they wish to switch.

At the end of high school, students can take the *Baccalaureate* exam. This national test is curriculum-specific and is high-stakes. Both passing the Baccalaureate—by passing each individual component, and receiving a Baccalaureate diploma—and obtaining a high score carry rewards. The diploma is typically an admission requirement for universities, and a high score helps secure admission to more prestigious schools, and to obtain scholarships. Even for non-university bound students, the Baccalaureate diploma and a high score can serve as labor market signals.

3.2 Variation in curriculum

The variation we use arises when individuals' ranked lists contain tracks with different curricula. For example, consider a set of students who rank a STEM track first and an HSS track second. Those close to the cutoff will then provide a good counterfactual in the spirit of a regression discontinuity: they will be similar except for the curriculum to which they are exposed. Similarly, a different set of individuals might rank HSS tracks first and STEM tracks second. The cutoffs between them will provide analogous analytic leverage to study the effects of curriculum.

A relevant question is why the variation we use arises. In other words, why might a student alternate her choices between STEM and HSS (e.g., STEM first, then HSS, then STEM)? This behavior reflects that tracks have attributes beyond the curriculum they teach.

For example, a given high school might have the best overall peer quality, the best reputation in its town, or an excellent location for a given student. Thus, some students might place attending that high school above their preferences for a given curriculum—they might be willing to go to any track in that school. Thus, they would list tracks with different curricula at that school consecutively in their preferences.

Previous evidence from Romania (Ainsworth et al. 2023) and Korea (Che et al. 2022), among other countries, suggests that students trade off curricular fit for other school characteristics, including selectivity and prestige. In fact, in our administrative data, 75 percent of students rank both STEM and HSS tracks among their choices, while 50 percent of students rank both types of tracks among their top five choices (see Appendix A1, page 41).

It is worth noting that female students are well-represented in our data, both in high school in general and in STEM subjects in particular. Like in many former communist countries, the gender STEM gap in schooling is relatively low.[10] Indeed, in our RD sample, females make up 55 percent of students ranking STEM over HSS at a cutoff and make up 58 percent of the students ranking HSS over STEM.[11]

can only transfer to a class if the number of students does not exceed 30.

10. For example, some 40 percent of tertiary graduates in STEM fields are women (World Bank 2023).

11. High school is compulsory and high school graduation rates are above 80% (UNESCO Institute for Statistics

3.2.1 University System

After high school, Romanian students can transition to university, the most prestigious of which are public.[12] In most cases, the track followed in high school does not restrict what students can study in college.[13] Most university programs uniquely rely on the baccalaureate grade for admissions, and the type of high school track a student graduated from is not typically a restriction. However, some of the most selective programs do organize admission exams, testing curriculum-specific subjects.

As is mostly the case outside the U.S., students enroll in a major immediately upon entering university, and immediately focus on relatively specialized classes. As they are admitted, students are ranked by their university admission scores and grouped into three categories. The top students get a "full ride": tuition wavers, free or discounted dorm rooms, and sometimes stipends. The second tier receives tuition wavers, and the lowest-scoring students must pay tuition and all other costs out of pocket.[14] These rankings are updated after each year, so both admission scores and GPA have a bearing on schooling costs. Therefore, the end-of-high-school Baccalaureate exam is both high-stakes for university admissions, but also in determining the student's tuition status. Lastly, it should be noted that STEM careers, in particular IT, are coveted as the highest-earning careers, and workers in the IT industry pay no income taxes.

3.3 Data

In this subsection we describe the administrative data we use and the three rounds of surveys we implemented.

3.3.1 Administrative Data

Our first data source comes from administrative records of the universe of students admitted to high schools in 16 of the 41 counties in Romania.[15] These data include the 2015-2017 and 2019 admission cohorts and contain information on basic demographics, students' middle school (grade 5 to 8) GPA, their scores on the national high school admission exam, their transition score (an average of the GPA and admission exam scores) used in the high school allocation mechanism, the set of all high school choices submitted, as well as the assigned high school track.[16]

We merged these data with two additional administrative sources. The first provides information on enrollment histories during high school and includes data on dropout, grade repetition,

2024). Moreover, since girls have higher achievement levels than boys (World Bank 2022), they are overrepresented in selective, academic tracks in high school.

12. The tertiary enrollment rate for the university-aged cohorts in Romania was 58 percent in 2022 (Bank 2025).

13. 41 percent of the students cited difficulty to change fields of study from high school to college as a reason for college major choice (Table A62). This is among the last-cited reasons.

14. There are separate financial aid packages for lower income students.

15. Romania is organized into 8 macro regions, and we selected 2 counties per region for a balanced geographical representation.

16. The 2018 admission cohort is excluded because of a reporting issue in that year.

and any transfers within school tracks and across schools. The second includes performance on the Baccalaureate exam, including exam retake information for students who did not pass. On average, each cohort has about 50,000 students who choose among roughly 1,300 tracks. Appendix Table A1 (page 41) provides summary statistics for the administrative data: the average transition score is 7.57 and the average GPA in middle school is 8.90 (both on a scale from 1 to 10) and the sample is 50% female.

3.3.2 (Baseline) End-of-high-school survey

We implemented our first survey in May 2023 by visiting the high schools in our administrative sample from the 2019 admission cohort. For this cohort, we administered a questionnaire one month before high school graduation and the Baccalaureate exam. The purpose of the survey was to collect information on school and track experiences and satisfaction, academic beliefs and preferences, college plans, non-cognitive traits, and time use. In total, we collected data from over 10,000 students who were close to STEM and HSS cutoffs, from 292 schools across 94 towns. We also collected tracking information to be able to follow up with students after graduation from high school.

3.3.3 Follow-up surveys

In Spring 2024, we surveyed the 2023 end-of-high school sample by phone. The main purpose of this survey round was to study their transition between high school and college. Our survey questions focused on the baccalaureate exam, the college admission process, college major choices as well as students' experiences during the freshman year. More than 2,000 students completed our survey. In appendix A2, we show that for this and subsequent surveys, there is no evidence of selection into answering the surveys based on observables.

To increase sample size, we also implemented a peer module in which asked students questions regarding our main outcomes of interest (baccalaureate exam, college admission and college major) about their classroom peers in senior year of high school. In this way, even if a student did not answer our follow-up survey, we could obtain information about them from their peers, typically corroborated by several peers. More than 1,700 students answered questions about more than 6,300 of their peers in this survey.

In Autumn 2024, we implemented a final follow-up survey with the same target sample. This second follow-up survey was focused on college experience during the sophomore year and an expanded module on career choices and beliefs. As part of this survey, we included a abridged version of the O*NET Interest Profiler, a career assessment tool that helps individuals identify their work-related interests and find occupations that match those interests.[17] The Autumn 2024

17. The O*Net Interest Profiler was developed by the U.S. Department of Labor and is based on Holland's RIASEC model (Holland 1997), which categorizes work interests into six broad areas (Realistic, Investigative, Artistic, Social, Enterprising and Conventional).

follow-up survey also included a module to measure non-cognitive outcomes and time-use during college. Overall, just over 3,000 students responded to this survey.

4 Methodology

4.1 Empirical Strategy

Our identification strategy is a regression discontinuity design using data from students' preference rankings over high school tracks. We restrict attention to students who are assigned to a STEM or HSS track. Since we are interested in the effects of field of study, we focus on students whose admission scores are close to and on either side of cutoffs where they would be assigned to a track with a different curriculum if their transition score were above or below the cutoff.

For a given student, there can be up to two relevant cutoffs: i) the lowest cutoff where, if a student scored higher than their transition score, the curricular focus of the track they attend would switch from STEM to HSS or vice versa and ii) the highest cutoff where if the student scored lower than their transition score, they would switch between STEM and HSS.

For example, suppose a student with an 8/10 transition score ranks four tracks: i) a STEM track with a cutoff of 8.10, ii) an HSS track with a cutoff of 7.90 and iii) an HSS track with a cutoff of 7.85 and iv) a STEM track with a cutoff of 7.80. This student would be admitted to their second-choice HSS track. If they had obtained a slightly higher score (8.10/10), they would have been admitted to their first-choice STEM track instead. Had the student scored slightly lower (below 7.90/10), they would have fallen back to their third-choice HSS track. However, we are not interested in this particular cutoff, as scoring above or below it does not change the curricular focus of the track attended by the student (HSS). However, if the student scored below 7.80, they would fall into their fourth-choice STEM track. Therefore, the two relevant cutoffs for this student are the 8.10 STEM cutoff and the 7.80 cutoff above which they scored. These cutoffs are the ones at which the curricular focus of the track attended by the student changes if they score above or below the cutoff.

These two relevant cutoffs may not exist for all students. For instance, the first cutoff will not exist if a student would never be assigned to a track with a different field of study by having a higher transition score. This could happen if a student never ranks tracks with a different curricular focus than their assigned track higher than this assigned track.[18] Or, this could happen if these higher-ranked tracks are unattainable (because the student ranked tracks with lower cutoffs higher, making lower-ranked choices with higher cutoffs unattainable). In a similar vein, the second cutoff will not exist if the student would never be assigned to a track with a different field of study by having a lower transition score.

We estimate a regression discontinuity model at the student-cutoff level. More formally, we

18. As noted previously, 75 percent of students in our sample rank both STEM and HSS tracks among their preferences.

stack the relevant student-cutoff observations, and we define the index i to be a student who is admitted to high school track a_i in year y_i. For every relevant student-cutoff combination, let j (k) be the track that student would attend if they score above (below) the cutoff. Also, let the cutoff score be written c_j—this is the transition score for the last student admitted to track j—and let the curricular focus of a track j be f_j. Finally, let Y_i be an outcome for i.

After identifying the relevant cutoffs for each student, we categorize the student-cutoffs into two types: i) cutoffs at which the student would be assigned to a STEM track if they score above the cutoff and HSS if they score below ($f_j = \mathrm{S}$ and $f_k = \mathrm{H}$), which we refer to as "STEM above") and ii) cutoffs at which the student would be assigned to a HSS track if they score above the cutoff and STEM if they score below ($f_j = \mathrm{H}$ and $f_k = \mathrm{S}$), which we refer to as "HSS above".

Then, we allow the running variable to differ by type of cutoff. For STEM above, the running variable r_i is the student's transition score (t_i) minus the cutoff score ($r_i = t_i - c_j$). For HSS above, the running variable is the cutoff minus the student's transition score ($r_i = c_j - t_i$). Using this setup, the running variable is always positive when the student is assigned to a STEM track and negative when the student is assigned to an HSS track, regardless of the type of cutoff (STEM above or HSS above). Intuitively, the running variable can be described as how far a student's admission score is from the STEM admission side of the cutoff.

In our analysis, we include fixed effects $\alpha(f_j, c_j, y_i)$ for the intersection of i) cutoff type (defined by the curriculum of the track above the cutoff f_j), ii) cutoff score (c_j) and iii) year of admission (y_i). We call these cutoff fixed effects. We also control for a linear spline in the running variable that varies with cutoff type and is separate for each side of the discontinuity: $h_\alpha(f_j, r_i)$. Our coefficients of interest are an indicator for being on the STEM side of the cutoff (i.e. $r_i > 0$) interacted with the cutoff type (defined by the curriculum f_j). We also drop student-cutoff combinations where the student's transition score is equal to the cutoff score (because different tie-breaker rules apply) or more than a given bandwidth away from the cutoff score.

Then the first-step (sharp) RD model is:

$$\mathrm{Y}_i = \alpha_S \mathbb{1}\{f_j = S\}\mathbb{1}\{r_i > 0\} + \alpha_H \mathbb{1}\{f_j = H\}\mathbb{1}\{r_i > 0\} + \alpha(f_j, c_j, y_i) + h_\alpha(f_j, r_i) + \epsilon_i \qquad (1)$$

Here, α_S and α_H measure the effects of being assigned to a STEM track when the curriculum of the track above the cutoff is STEM and HSS, respectively. The cutoff fixed effects are captured by $\alpha(f_j, c_j, y_i)$ and the cutoff type-specific linear splines are estimated by $h_\alpha(f_j, r_i)$, where we estimate different splines on either side of the cutoffs and where the splines vary by cutoff type.

To estimate the average treatment effect (ATE) of being assigned to STEM, we calculate a simple arithmetic average of being assigned to STEM when STEM is above and, respectively, below the cutoff (α_S and α_H). Intuitively, we would obtain the same coefficient estimates if ran separate regressions by cutoff type. However, estimating a single regression allows us to

calculate the standard errors for the ATE of STEM using our entire sample and the combined covariance matrix. We cluster standard errors two ways, by student and cutoff. We return to the interpretation of our estimates — and what they measure — in the next section.

In appendix A2, we conduct three validity tests for our analysis. First, using the methodology of Cattaneo, Jansson, and Ma (2020), we show that there is no evidence of running variable manipulation. This is expected because grading of the transition exams occurs in different towns than the ones students reside in, and cutoffs are endogenously determined by the allocation mechanism after student preferences and scores are collected. Second, we check that our key covariates are balanced on either side of cutoffs. Finally, we show that there is no evidence of selection based on observables into our survey samples.

4.2 Discussion of the Empirical Strategy

As previously mentioned, our empirical strategy estimates an average of two separate effects: being assigned to a more selective STEM track (above the cutoff), and being assigned to a less selective STEM track (below the cutoff). These effects are measured relative to being assigned to the HSS track that is on the other side of the cutoff.

There are three "sub-treatments" associated with being admitted to a STEM track versus a HSS track close to a cutoff. First, sub-treatment (a) is that the curriculum is different. As discussed previously, students in STEM are exposed to radically different curricula — involving more mathematics and science hours of instruction, but fewer language, humanities and social studies courses — compared to HSS students.

Second, being assigned to a STEM field also means exposure to a different set of peers and teachers (sub-treatment b). Setting aside aggregate admission scores, STEM peer groups tend to be more interested in — and perhaps better at — STEM subjects, have different career aspirations, and potentially exhibit different gender compositions compared to those in HSS. intuitively, these features are "baked into" a STEM track and are part of the treatment as much as the STEM curriculum.

Lastly, scoring above or below a cutoff implies being admitted to a track with higher- or lower-achieving students (sub-treatment c). Moreover, a student who scores just above a cutoff is likely to be among the lowest-scoring student in a track, while a student who scores just above is likely to be among the top-scorers. This can obviously have implications on the student's performance via self-efficacy or teacher perceptions of students. We quantify the effect of assignment to different tracks on observable peer characteristics in the first section of our results.

From a policy perspective, one can argue that we are most interested in measuring the curriculum effect (a), as this would reveal the impact of reforms aimed at increasing STEM — or HSS — instruction hours for all students. These reforms are possibly the most scalable — although more STEM teachers would need to be hired to absorb the aggregate increase in STEM

instruction hours — and do not involve reshuffling students across different curricula, which may have general equilibrium implications.

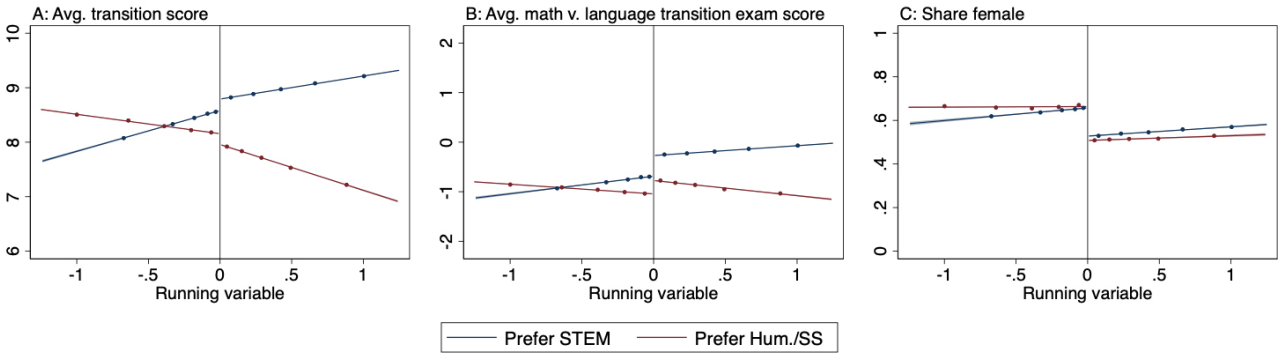
Additionally, we might be interested in the combined effects of exposure to a curriculum and exposure to peers who are more interested in that particular curriculum (a and b). This treatment relates to the decision (e.g. in college) that households face when choosing one type of field versus another.

We are least interested in the effects of attending a more or less selective track (c). This is an interesting question in its own right and has been studied in the past — for example, by Pop-Eleches and Urquiola (2013) — but is otherwise unrelated to the question of field of study. Thus, variation in peer quality serves only as a confounding factor in assessing the impact of curriculum choice.

Our estimation strategy allows us to estimate the effects of the curriculum (a) and the nature of peers and teachers (b), while eliminating the effects of track selectivity (c). This is the case because we average out the scenarios where STEM is above the cutoff and the scenarios where STEM is below the cutoff. In this way, we average out the effects of being admitted to a more selective track, with the effects of being admitted to a less selective track. Thus, our ATE is the combined effect of (a) and (b). It reveals the impact of choosing between equally selective STEM and HSS tracks, holding constant any general equilibrium impacts on the nature of peers. Below, we conduct extra analyses to try to disentangle the effects of the curriculum from the effects of exposure to peers, but we cannot do so fully.

5 Effects on attributes of students' assigned tracks

Figure 1: RD illustration: effects on peer quality and share female in students' assigned tracks



The figure provides a graphical illustration of the RD treatment effect. Prefer STEM is for students at STEM above-HSS below cutoffs. Prefer HSS is for students at HSS above-STEM below cutoffs. The running variable is a student's transition score minus the cutoff score for Prefer STEM and the cutoff score minus the student's transition score for Prefer HSS. We residualize the outcome variables on cutoff fixed effects and then add back the mean of the fixed effects. The effect of being assigned to STEM for Prefer STEM (Prefer HSS) is the vertical difference in the blue (red) lines at a running variable value of 0. The average treatment effect of STEM is the simple average of the two vertical differences. The sample is the 2015-2017 and 2019 cohorts. Variables are from the administrative data.

We begin by examining the effects of assignment to STEM or HSS on the attributes of tracks students are assigned to. As noted earlier, being placed in tracks with different curricula inherently alters peer group composition. To the extent that exposure to different peers affects student behaviors, the ATE of track assignment partly captures peer effects.

In Figure 1, we graphically show the effects of being assigned to a STEM or HSS track on i) peer ability, ii) relative ability of peers in mathematics and languages, and iii) the share of female peers. We show these effects around the admission score cutoffs, separately for cases where STEM tracks are above the cutoff and HSS tracks are above the cutoff. These figures also serve to graphically illustrate the treatment effects we estimate throughout this paper.

In panel A, we show how peer ability, measured by their middle school to high school transition score, varies at the cutoffs. The blue line relates to the case where students are close to the cutoff to a STEM track, which they prefer, while the fallback track is a less selective HSS track.[19] If the students score above (to the right of) the cutoff, they are admitted to the STEM track and their peers have higher average transition scores. Likewise, if they score below (to the left of) the cutoff, they are admitted to the less selective HSS track, where their peers have lower average transition scores.

The red line relates to cases where students prefer an HSS track to a fallback STEM track. As detailed in the previous section, the running variable in our regression is set up such that it always takes positive values when student are assigned to STEM. This means that the "STEM side" of the graph is always the one to the right of the cutoff in our figures. When students prefer the HSS track, this right side of the graph is associated to having a score *below* the cutoff — and being assigned to STEM — and the left side is associated to having a score above the cutoff and being assigned to HSS. In this case, STEM assignment is associated with lower average transition scores, since the STEM track is less selective than its HSS counterpart.

Graphically, the treatment effect we measure in our model is the average of two effects: i) the vertical jump in the blue line at the discontinuity (α_S in equation 1) and ii) the vertical jump in the red line at the discontinuity (α_H in equation 1). These effects are also shown in Table 2. Peers above a STEM cutoff score 0.21/10 points higher on the transition exam, while those above an HSS cutoff score 0.22/10 higher. Since we are averaging cases where STEM is more selective and less selective, the overall effect of STEM assignment on the average transition score of students' peers is null.

In panel B, we show that when students are assigned to STEM tracks, their peers are unsurprisingly relatively stronger at math than at languages: they score more on the math component of the transition exam than on the language components. This is true irrespective of how selec-

19. Note that the fallback track must always be less selective than the preferred cutoff track by construction. Otherwise, if their score is too low for the cutoff track, it will also be too low for the fallback track, making the choice of the fallback track irrelevant in practice.

Table 2: Effects on attributes of students' assigned tracks

	Average		Share Female
	Transition score	Math v. language transition exam score	
Panel A: Average treatment effects			
STEM	-0.007	0.357***	-0.150***
	(0.007)	(0.010)	(0.004)
Intercept	8.33	-0.89	0.66
Std. dev.	0.92	0.75	0.15
Cutoffs	1,904	1,904	1,904
Students	62,301	62,301	62,301
Student-cutoffs	73,470	73,470	73,470
Panel B: Effects for students who prefer STEM			
STEM	0.207***	0.429***	-0.135***
	(0.010)	(0.015)	(0.006)
Intercept	8.54	-0.73	0.66
Std. dev.	0.75	0.66	0.15
Cutoffs	973	973	973
Students	37,376	37,376	37,376
Student-cutoffs	37,376	37,376	37,376
Panel C: Effects for students who prefer Hum./SS			
STEM	-0.221***	0.284***	-0.166***
	(0.010)	(0.012)	(0.005)
Intercept	8.13	-1.05	0.66
Std. dev.	0.91	0.73	0.15
Cutoffs	931	931	931
Students	36,094	36,094	36,094
Student-cutoffs	36,094	36,094	36,094

The table shows effects on attributes of students' assigned tracks. 1.25 point bandwidth. The sample is the 2015-2017 and 2019 cohorts. Intercept is the mean value of the outcome for students at the cutoff who get assigned to HSS. Std. dev. is the standard deviation of the outcome among students within the RD bandwidth (i.e., within 1.25 points of the cutoff). Standard errors are clustered in two ways by student and cutoff.

tive the STEM track is compared to the HSS track at the cutoff; on average, peers score 0.43/10 higher on the math component when STEM is above the discontinuity, versus 0.36/10 higher when STEM is below the discontinuity. Therefore, the effect of having peers who are relatively better at math is part and parcel of the treatment students are subject to when they are assigned to STEM tracks. Similarly, in panel C, we show that the share of female peers is lower on the STEM side of the cutoff, irrespective of which track is more selective. Overall, STEM tracks contain 15 pp fewer female peers at the cutoffs.

Therefore, the ATE of exposure to a STEM track includes exposure to different courses and teachers, but also encompasses exposure to peers who are relatively more able in math versus languages (panel B), and exposure to classes with more female students (panel C). However, the ATE we measure is net of being exposed to more or less able peers (panel A). As discussed previously, this is useful, because we are interested in the effect of exposure to a curriculum, and

not in the effect of attending a more or less selective track.

In later sections, we attempt to further disentangle the treatment effect by isolating peer effects from other curriculum effects using a survey. Although we cannot entirely disentangle the effects of curriculum from peer effects, we mostly rule out that peer effects are driving our results.

6 Effects on high school enrollment and performance

In this section we examine the effect of assignment to a STEM high school track on students' graduation and baccalaureate exam performance.

6.1 Exposure and graduation

We begin by showing how assignment to STEM affects how long students stay in school and what types of tracks they enroll in and their graduate from. Column 1 of Table 3 shows that assignment to STEM does not affect the time students spend in high school: the coefficient on overall years of enrollment is close to zero and insignificant.

Table 3: Effects on enrollment and graduation

	Years of enrollment				**Graduate**			
	All	STEM	Hum./SS	Technical	All	STEM	Hum./SS	Technical
STEM	0.002	3.08***	-3.09***	0.015**	-0.003	0.694***	-0.703***	0.007***
	(0.007)	(0.023)	(0.023)	(0.006)	(0.003)	(0.007)	(0.008)	(0.002)
Intercept	3.91	0.50	3.36	0.05	0.96	0.16	0.80	0.01
Std. dev.	0.41	1.89	1.88	0.36	0.18	0.50	0.49	0.12
Cutoffs	1,411	1,411	1,411	1,411	1,411	1,411	1,411	1,411
Students	46,789	46,789	46,789	46,789	46,789	46,789	46,789	46,789
Student-cutoffs	55,221	55,221	55,221	55,221	55,221	55,221	55,221	55,221

The table shows effects on high school enrollment and graduation. 1.25 point bandwidth. The sample is the 2015-2017 cohorts. Outcomes are measured within four years of track assignment. Variables are from the administrative data.

However, students assigned to a STEM track experience, on average, 3.1 years of additional enrollment in a STEM-oriented curriculum (column 2)—a large increase relative to a mean of 0.5 years for the reference group of HSS students. There is little effect on graduating from a technical/vocational track, which caters to non-postsecondary-bound students. Not surprisingly, these students experience 3.1 *fewer* years of exposure to HSS curricula (column 3); again, a large decline relative to 3.4 years for HSS students.[20] These last two estimates are highly statistically significant. In short, assignment to STEM has a major effect on students' high school coursework.

Columns 5-8 refer to graduation and tell a similar story. Assignment to STEM does not affect a student's overall graduation probability (column 5). However, students assigned to STEM tracks are much more likely to graduate from a STEM curriculum and much less likely to

20. As previously mentioned, switching to a track with a different curriculum is possible, but constrained by admission scores and, after the first year, by additional exams.

graduate from an HSS one. The respective changes in probability (about 70 pp) again represent a large effect: e.g., a student assigned to STEM is more than four times as likely to graduate from STEM as one who is not.[21]

To summarize, assignment to STEM has a clear and consistent "first stage" impact on students' high school experience.

6.2 Baccalaureate performance

We next examine how STEM assignment affects students' performance on the high-stakes end-of-high school Baccalaureate exam. As noted previously, the baccalaureate exam is curriculum-specific, meaning that STEM and HSS students write different versions of the baccalaureate exam. For example, STEM students take Romanian, math and a science component of the baccalaureate, while HSS students take Romanian, history and a HSS component. Even the Romanian components of the exam are different for the two tracks, emphasizing: for STEM students, argumentation is emphasized, while literary analysis is the focus for HSS.

Table 4 (page 19) shows that being assigned to a STEM track makes students less likely to take the exam (column 1). This effect is statistically significant but relatively small—about a one percentage point decline on an average probability of 95 percent. Conditional on taking the exam, students assigned to STEM perform worse. The probability of passing falls by about 4 pp compared to HSS students, who pass at an average rate of 92 percent (column 2). Students assigned to STEM further see their exam scores decline by about a third of a standard deviation (column 3). Both of these negative effects are highly statistically significant. In short, STEM assignment lowers overall Baccalaureate performance.

Table 4: Effects on baccalaureate performance

	Take the exam	**Pass the exam**	**Exam score**	**Pass in**		
				STEM	Hum./SS	Technical
STEM	-0.011***	-0.036***	-0.351***	0.642***	-0.686***	0.005***
	(0.003)	(0.004)	(0.015)	(0.008)	(0.008)	(0.002)
Intercept	0.95	0.92	8.08	0.14	0.77	0.01
Std. dev.	0.21	0.29	1.21	0.50	0.49	0.10
Cutoffs	1,904	1,904	1,855	1,411	1,411	1,411
Students	62,301	62,301	59,127	46,789	46,789	46,789
Student-cutoffs	73,470	73,470	69,938	55,221	55,221	55,221

The table shows effects on performance on the end-of-high-school baccalaureate exam. 1.25 point bandwidth. Outcomes are measured within four years of track assignment. Variables are from the administrative data. The sample for the first two columns is the 2015-2017 and 2019 cohorts. The sample for "Exam score" is students from the 2015-2017 and 2019 cohorts who took the exam. The sample for the "Pass in" columns is the 2015-2017 cohorts, as we do not have enrollment data for the 2019 cohort.

21. These exposure and graduation effects are robust to: using different bandwidths, adding covariates, and allowing the outcomes to be measured over the entire length of our data rather than just within four years of track assignment (Appendix A4). In addition, there is little heterogeneity by track selectivity—the effects are similar whether students were close to the cutoff of very selective or less selective tracks.

Importantly, assignment to STEM nevertheless increases the probability that students write and pass the STEM version of the baccalaureate exam (columns 4-6). Relative to students who just miss getting assigned to a STEM track, those who do have a much higher probability of passing the STEM version of the bac—an effect of 64 pp above and beyond the 14 pp pass rates for students who were initially assigned to an HSS track. Correspondingly, assignment to STEM lowers the probability of passing in HSS by about 69 pp relative to the HSS assignees and has almost no effect on the probability of passing in Technical.

These results illustrate that being assigned to STEM induces a type of risk-reward tradeoff. On the one hand, graduation from STEM may entail positive returns, including in the labor market. On the other hand, STEM assignment increases the probability of failing the Baccalaureate exam—a salient risk in Romania, where failing forecloses academic-oriented tertiary education.

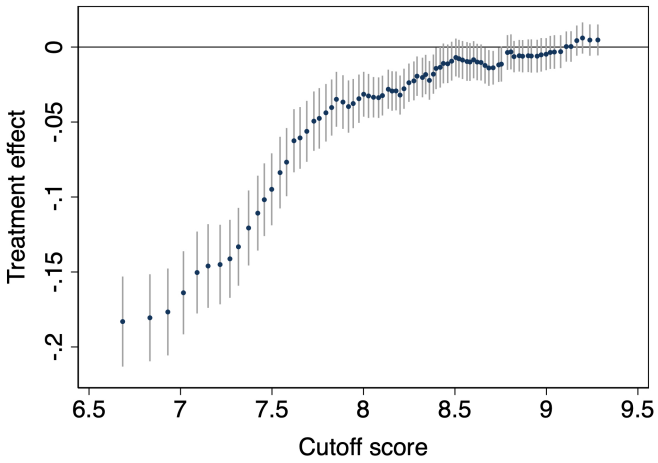
The negative effect on passing the baccalaureate for STEM students are most likely driven by the STEM version of the baccalaureate being more difficult. Two pieces of evidence validate this claim. First, students assigned to STEM assess that high school prepared them better for college (Table 13). Second, STEM students believe the bac exam is more difficult than HSS students do (Table A13 of the appendix). While this relative degree of difficulty is a particularity of the Romanian baccalaureate exam, we believe that this risk-reward tradeoff to STEM is a feature in many, if not most, high school and university systems around the world, where achieving good grades in STEM is more difficult. For example, in the U.S., college GPAs tend to be significantly lower in STEM than in humanities majors (Gorelick 2023; Rojstaczer and Healy 2023).

Figure 2 (page 21) elaborates on this risk. It shows how the effect STEM assignment has on the probability of passing varies with the cutoff scores determining STEM assignment. Toward the figure's left are cutoffs to less selective tracks, that switched lower-scoring students to STEM; towards the right are cutoffs to selective tracks, that affected high-scoring students. The treatment effect is on the y-axis; the dots indicate the point estimate, and the lines are the 95 percent confidence intervals.

The figure reveals that the negative impact is much larger for students at lower cutoffs. At these, STEM assignment reduces the probability of passing by close to 20 pp—a substantial effect. By contrast, high-achieving students take on less "STEM risk": for highly selective tracks, the effect is often close to zero and statistically insignificant.

Interestingly, the pattern in Figure 2 holds for all Baccalaureate-related outcomes: for taking, for passing, and for the score conditional on taking (Appendix A4). Thus, the reduction in the likelihood of passing in Table 4 arises not just because lower-achieving students are more likely to be near the threshold for passing, but also because they experience a larger reduction in their score. Further, this reduction is likely understated due to the negative effect on exam-taking.

Figure 2: Heterogeneity in effects on passing the Bacc. by cutoff score



The figure shows treatment effects on passing the bacc. exam for different samples. 1.25 point bandwidth. The samples always represent 20% of the full sample. The left-most point is for the least-selective quintile of cutoffs (weighted by the number of students within a cutoff's bandwidth). The other points are for samples that are shifted up the cutoff selectivity distribution by one percentile point. Treatment effects are plotted at the mean cutoff score in the sample. The blue dots are the estimated treatment effects, and the gray bars are 95% confidence intervals.

7 Effects on college plans and outcomes

The results thus far show that STEM assignment affects students' high school experiences and graduation profiles. One possibility is that the impact of STEM assignment ends there. In other words, that once students leave the high school building, the force of assignment—no longer tied to any power the high school has over the student—ceases to have an effect.

To begin exploring what happens as the direct/mechanical impact fades, we turn to the effects on students' post-high school career *plans*. Table 5, Panel A, (page 22) refers to students' intentions for college, as recorded in the survey administered at the end of high school (before students learned their Baccalaureate exam score). Columns 1-5 show that while being assigned to high school STEM has little effect on whether students plan to attend college (column 1), there is a large effect on planning to enroll in STEM in general and in math and computer science in particular. Specifically, the probability that students declare STEM plans rises by 23 pp (column 2), a large increase from a baseline value of 31% of HSS students. Similarly, the probability of expressing math/computer science increases by 15 pp (columns 3), more than doubling relative to a baseline level of 8% for HSS students. There are also positive, albeit smaller and less statistically significant, effects on medicine and economics/business (columns 4 and 5).

Not surprisingly, the remaining columns in Panel A show associated declines in the probability that individuals assigned to high school STEM express plans to attend college in humanities, law, and social science. All three show declines of roughly similar magnitude. Each cuts in about half (relative to the HSS students) the incidence of plans to pursue college in these areas. In

Table 5: Effects on college plans and enrollment

	Any	**STEM**				**Hum., law, & social science**				**Other/ unsure**
		Any	Math & CS	Medicine	Economics & Bus.	Any	Humanities	Law	Social science	
Panel A: College plans at the end of high school										
STEM	0.010	0.233***	0.147***	0.041*	0.046*	-0.224***	-0.075***	-0.057***	-0.092***	0.001
	(0.018)	(0.035)	(0.024)	(0.024)	(0.027)	(0.032)	(0.020)	(0.021)	(0.020)	(0.023)
Intercept	0.87	0.31	0.08	0.10	0.14	0.39	0.13	0.12	0.14	0.16
Cutoffs	293	293	293	293	293	293	293	293	293	293
Students	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987
Panel B: College enrollment one year after high school										
STEM	-0.037	0.246***	0.192***	0.015	0.039	-0.261***	-0.123***	-0.092***	-0.046***	-0.022
	(0.025)	(0.036)	(0.031)	(0.022)	(0.026)	(0.031)	(0.021)	(0.021)	(0.017)	(0.027)
Intercept	0.82	0.28	0.11	0.08	0.10	0.38	0.17	0.13	0.08	0.16
Cutoffs	280	280	280	280	280	280	280	280	280	280
Students	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978
Student-cutoffs	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327

The table shows effects on college plans and enrollment. 1.25 point bandwidth. Variables in Panel A are from the end-of-high-school survey. Variables in Panels B are from the follow-up or peer surveys.

short, Panel A presents an initial indication of some "malleability" in students' preferences and plans.

Panel B in Table 5 shows that this translates into realized outcomes; it displays results for college enrollment one year after high school graduation. Overall, being assigned to STEM reduces the probability that students enroll in college by a statistically insignificant 4 pp (column 1). However, there are substantial and statistically significant increases in STEM enrollment, particularly in math/computer science, with corresponding decreases in HSS, law, and social science. For the sake of space, we skip discussing the magnitudes of these effects but note that they align closely with the college plan results in Panel A.[22] Across panels, the results in Table 5 tell a consistent story: high school STEM assignment has persistent effects on students' intentions and realized outcomes.[23]

Next, we explore the heterogeneity in the effects of STEM exposure on college plans and enrollment. In Table A19 of the appendix, we show that there is relatively little heterogeneity in the effects of STEM exposure on plans and enrollment into college and STEM majors, compared to the very large average effects.

The overall effect on college plans and enrollment is statistically insignificant but slightly

22. In addition, similar results hold measuring college enrollment 1.5 rather than 1 year after high school graduation.

23. The results are similar for the different survey samples and are robust to using different bandwidths and covariates (Appendix A5). The results on enrollment are also similar when measured at the time of initial enrollment, one year after high school, or 1.5 years after high school.

larger for low-achieving students. This is consistent with earlier results, showing that lower-achieving students assigned to STEM tracks are more likely to fail the Baccalaureate exam, all but foreclosing entry paths into higher education.

By contrast, there is surprisingly little heterogeneity by students' initial preferences over STEM and relative ability in STEM at baseline. This suggests that matching students to curricula by baseline ability or interests is not nearly as important as one might think. Indeed, STEM exposure has similar effects on STEM major enrollment in students who, at the cutoff, preferred the STEM track (26 pp) or HSS (23 pp), nearly doubling the STEM enrollment rate observed in their counterparts assigned to an HSS track. The same applies to students scored relatively higher on the math component who see jumps in their college STEM enrollment of 22 pp. Meanwhile, students who preferred HSS at the cutoff experience a whopping 29 pp in their STEM enrollment, more than doubling their baseline levels of 21% enrollment. This is remarkable, and suggests that "hunger feeds the appetite" for STEM, since students who do not have a preference or particular affinity for STEM are nonetheless nudged towards STEM majors as much as students who *do* have a particular interest or ability in STEM. Truly, exposure to STEM trumps all other considerations, such as match effects, which a priori could have been important.

We also document heterogeneity by gender. Despite high school STEM tracks being a male dominated environment, with 15 pp higher proportions of male students, the effects of STEM exposure on college plans and enrollment vary relatively little by gender. We find that STEM exposure does lead to a positive effect (11 pp) on plans to attend college for male students, and no effect on girls' plans. One year after high school, however, we find that high school STEM has no effect on enrollment for males and a slightly negative effect (5 pp) on girls' enrollment in college, relative to a baseline enrollment rate in university that is higher for female students (84%) than male students (76%) in our sample. The overall differences between plans and actual enrollment possibly reflect the particularly competitive nature of admissions in STEM. Lastly, when it comes to enrollment into STEM majors, boys see a higher boost (28 pp) than girls (21 pp), relative to baseline rates of enrollment into STEM of roughly 30%.

8 Effects on academic beliefs and preferences

We have shown, thus far, that STEM exposure influences students' college plans and outcomes. There are a variety of mechanisms that could account for these results. For example, exposure could make students more confident about their STEM abilities and/or lead them to develop a taste for STEM coursework. Conversely, students might not gain confidence and dislike STEM, but they may feel that they have sunk too much into that path to abandon it.[24]

Table 6 (page 24) explores these possibilities by considering the effect of STEM assignment

24. This type of reaction has been studied in the literature [Paper on mismatch by Yeon-Koo et al.]

on students' beliefs about their abilities. In Panel A, the dependent variable is a score (ranging from 1-5) by which students self-assess their ability in different areas. The estimates show that being assigned to STEM makes students believe they are stronger in STEM and weaker in HSS subjects. Specifically, students' scores in STEM rise by about 0.7 standard deviations, a substantial effect. At the other extreme, students' self-assessment of their ability in social studies falls by about 0.5 standard deviations. Panel B shows that these effects persist one year after high school graduation.

Table 6: Effects on beliefs about own abilities and preferences for high school subjects

	STEM subjects	**Humanities subjects**	**Social science subjects**
Panel A: Beliefs at the end of high school			
STEM	0.873***	-0.235***	-0.565***
	(0.077)	(0.064)	(0.074)
Intercept	2.60	4.07	3.98
Std. dev.	1.29	0.90	1.15
Cutoffs	293	293	293
Students	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987
Panel B: Beliefs one year after high school			
STEM	0.744***	-0.267***	-0.745***
	(0.124)	(0.087)	(0.139)
Intercept	2.96	4.20	4.06
Std. dev.	1.10	0.84	1.13
Cutoffs	190	190	190
Students	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159
Panel C: Preferences one year after high school			
STEM	1.01***	-0.405***	-0.697***
	(0.151)	(0.102)	(0.135)
Intercept	2.72	4.13	4.08
Std. dev.	1.37	1.04	1.21
Cutoffs	190	190	190
Students	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159

The table shows effects on students' beliefs about their abilities in different high school subjects and students' preferences for high school subjects. 1.25 point bandwidth. Variables in Panel A are from the end-of-high-school survey. Variables in Panels B and C are from the follow-up survey.

Panel C shows that beyond beliefs, treatment affects students' preferences for STEM expressed after high school. The panel uses a similar score, and shows that STEM assignment raises students' preference for STEM by about 0.7 standard deviations. The language and social science reductions are similar to those observed in the previous panels.[25] These effects hold for

25. It is worth noting that there is a statistically significant decline in these scores between our baseline and follow-up surveys. However, this decline is insufficient to change the overall result of a positive impact of stem assignment on beliefs and preferences.

different types of students, including men, women, and low- and very high-achieving students.[26]

The questions in Table 6 (page 24) asked respondents about their ability as relevant to high school subjects. These questions cover our entire survey sample because everyone in it attended high school. We also have results for college subjects, but they are subject to some sample selection because some students never attended college (and being assigned to STEM slightly reduces the probability of attending college, as shown above). To deal with selection we impute score values of 1 for students who never attended college; the results are quite similar to those in Table 6.

Finally, Table 7 shows that the change in preferences and self-beliefs about ability extend to *college* subjects as well. The results are very similar to the ones observed with respect to high school subjects: STEM assignment leads to a 1.4 sd increase in self-beliefs about ability in college STEM subjects and 1.5 sd increase in preferences over these subjects, with similar declines in preferences and beliefs about subjects that involve reading, writing and memorization.

Table 7: Effects on beliefs about own abilities and preferences for college subjects

	STEM subjects	**Subjects that involve reading and writing**	**Subjects that involve memorization**
Panel A: Beliefs one year after high school			
STEM	0.659***	-0.396**	-0.278*
	(0.151)	(0.154)	(0.153)
Intercept	2.57	3.23	3.17
Std. dev.	1.39	1.32	1.32
Panel B: Preferences one year after high school			
STEM	0.776***	-0.525***	-0.372**
	(0.149)	(0.164)	(0.157)
Intercept	2.48	3.24	3.06
Std. dev.	1.45	1.31	1.31
Cutoffs	190	190	190
Students	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159

The table shows effects on students' beliefs about their abilities in different college subjects and students' preferences for college subjects. 1.25 point bandwidth. Variables are from the follow-up survey. The questions were asked only to students who either currently attend or have attended college (at the time of the follow-up survey); we impute values of 1 for students for whom the questions were not asked. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

9 Effects on career plans

The results in the previous section show that STEM assignment influences students' beliefs and preferences; hence, it likely also affects their career plans. Consistent with this, Table 8 (page 26) shows that being assigned to STEM raises the probability that students plan careers in STEM

26. The results are similar for the different survey samples and are robust to bandwidths and covariates; see (Appendix A6). Effects exist for all types of students, including female v. male students and low- v. high-achieving students.

— including business and economics — by 17 pp, a substantial effect relative to a baseline level of 60 pp for HSS students. The effect is even larger for technology/engineering: 25 pp over and above a baseline level of 10 pp for their HSS counterparts (column 2). By contrast, the effects on medicine and economics/business are negligible. Also consistent with shift to STEM-related careers, there is a substantial negative effect on students' desire to pursue careers in art, education, law, or social services.[27]

Table 8: Effects on career plans one year after high school

	STEM				**Art, education, law, or social services**	**Other/ unsure**
	Any	Tech or engineering	Medicine	Economics & Business		
STEM	0.173***	0.254***	-0.041	-0.040	-0.145***	-0.028
	(0.056)	(0.051)	(0.044)	(0.063)	(0.046)	(0.040)
Intercept	0.60	0.10	0.17	0.33	0.23	0.17
Cutoffs	190	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159	1,159

The table shows effects on career plans. 1.25 point bandwidth. Variables are from the follow-up survey.

While there is some heterogeneity in career plans as a result of STEM exposure, the main takeaway remains that STEM exposure greatly increases the STEM career plans of all groups of students. The effects are somewhat smaller if the student initially preferred HSS at high school admissions (14 pp) versus STEM (21 pp). The effects are smaller for women (14 pp) versus men (24 pp). This is almost entirely driven by a larger boost for men in pursuing tech and engineering careers.

Table 9 (page 27) uses our second follow-up survey to examine on the effects of STEM assignment on career choices and beliefs 1.5 years after high school graduation. Each panel considers students' beliefs about one career; Panel A focuses on IT, technology, or engineering work, Panel B on being a humanities teacher, and Panel C on running a business.

Being assigned to high school STEM significantly increases the probability that students indicate that they would choose IT/tech/engineering work, find it enjoyable, be well prepared, and feel that their friends and family would approve. These answers are consistent with STEM assignment affecting people's preferences. For example, the coefficient on enjoying the work (column 3) is equivalent to 0.24 standard deviations, and that on the desire for such a job is 0.7 standard deviations. The treatment does not affect students' belief that STEM would pay well, in essence because most respondents believe that a STEM career would pay well and that belief is not greater among those in the treatment rather than the control group. There is also no treatment effect on the belief that one would have good co-workers and work conditions.[28]

27. These results are robust to variations in the bandwidths and covariates.

28. Results are robust to bandwidths and covariates. In terms of heterogeneity, effects are smaller (but still

Table 9: Effects on career choices and beliefs 1.5 years after high school

	Would choose	**Good pay**	**Enjoyable work content**	**Good coworkers & work conditions**	**Well prepared**	**Friends & family would approve**
Panel A: An IT, tech, or engineering worker						
STEM	0.146***	0.037	0.614***	0.185	0.543***	0.336**
	(0.047)	(0.077)	(0.185)	(0.157)	(0.199)	(0.135)
Intercept	0.20	4.50	2.58	3.20	2.60	4.05
Panel B: A humanities teacher						
STEM	-0.054	0.019	-0.153	0.022	-0.371**	0.149
	(0.049)	(0.082)	(0.151)	(0.139)	(0.148)	(0.166)
Intercept	0.18	2.82	2.26	2.86	2.70	3.52
Panel C: A person who runs a business						
STEM	-0.092	0.066	-0.090	-0.152	-0.336***	-0.086
	(0.061)	(0.113)	(0.142)	(0.124)	(0.115)	(0.108)
Intercept	0.62	4.19	4.20	4.18	3.96	4.49
Cutoffs	198	198	198	198	198	198
Students	1,089	1,089	1,089	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199	1,199	1,199	1,199

The table shows effects on career plans. 1.25 point bandwidth. Variables are from the second follow-up survey.

Panels B and C show that assignment to STEM mostly does not affect students' beliefs about the two other careers: humanities teacher and business manager. This seems to be because, as expected, STEM graduates feel less prepared for these careers.

Finally, in Table 10, we extend our analysis of the effect of exposure to STEM on career preferences, by exploring the responses to the O*NET Interest Profiler module. As mentioned earlier, this career assessment tool is based on a series of questions that asks individuals to indicate interests in certain work activities, irrespective of their current qualifications for such tasks. This module is based on Holland's RIASEC model (Holland 1997) and breaks down work interests into six personality types (Realistic, Investigative, Artistic, Social, Enterprising and Conventional). For each group, we included 3 questions from the original survey and created a personality specific score. We also grouped STEM related personalities (Realistic, Investigative, Enterprising and Conventional) and HSS personalities (Artistic, Social) into separate indices. The results in Table 10 indicate that exposure to STEM changes graduates' preferences and their perceived fit for related careers. There is a statistically significant increase in work interests that are STEM related (driven by Investigative and Conventional personality types) and also a decrease in work interests linked to HSS. The results are similar for both male and female

present) for students who initially preferred HSS and for females. For both low- and high-achieving students, there is a similar reduction in art, education, law, or social services plans. But for high-achieving students, the shift is entirely into technology and engineering, while for low-achieving students it is split between technology/engineering and economics/business.

students (Table A30).

In short, we find indication that exposure to STEM changes graduates' preferences and their perceived fit and for related careers, which again points to some "malleability" in these areas.

Table 10: Effects on preferences over O*NET job activities 1.5 years after high school

	STEM-related					**Hum./SS-related**		
	Any	Realistic	Investigative	Enterprising	Conventional	Any	Artistic	Social
STEM	0.828***	0.140	0.327**	0.102	0.259**	-0.371*	-0.192	-0.180
	(0.288)	(0.119)	(0.136)	(0.096)	(0.116)	(0.220)	(0.158)	(0.120)
Intercept	6.60	0.92	1.77	2.36	1.54	3.80	1.54	2.26
Std. dev.	2.65	1.00	1.35	0.97	0.92	1.65	1.18	0.88
Cutoffs	198	198	198	198	198	198	198	198
Students	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199

The table shows effects on career plans. 1.25 point bandwidth. Variables are from the second follow-up survey.

10 Effects on satisfaction, fit, and regret

We turn now to exploring graduates' retrospective satisfaction with the high school experience after graduation, in Table 11 (page 28) Panel A at the end of high school and in Panel B one year later in our first follow-up. The results suggest that it is possible to direct students toward STEM without major consequences on their satisfaction or feelings of academic fit.

Table 11: Effects on high school satisfaction and curricular fit

	Liked the:				**Curriculum was good fit**
	Experience	Curriculum	Peers	Teachers	
Panel A: End of high school					
STEM	0.113*	0.002	0.233***	-0.022	0.001
	(0.068)	(0.066)	(0.072)	(0.068)	(0.053)
Intercept	3.69	3.32	3.53	3.60	3.39
Std. dev.	0.99	1.04	1.12	1.02	0.86
Cutoffs	293	293	293	293	293
Students	3,562	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987	3,987
Panel B: One year after high school					
STEM	0.217*	-0.004	0.287**	0.128	-0.123
	(0.110)	(0.137)	(0.138)	(0.130)	(0.118)
Intercept	3.90	3.13	3.82	3.75	3.49
Std. dev.	0.89	1.06	1.08	0.93	1.02
Cutoffs	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159

The table shows effects on high school satisfaction and curricular fit. 1.25 point bandwidth. Variables in Panel A are from the end-of-high-school survey. Variables in Panel B are from the follow-up survey.

In particular, Panel A indicates that at the end of high school, STEM assignment does not

affect whether a student liked the high school experience, her teachers, the curriculum (in general or in terms of fit). The key exception concerns peers: students assigned to STEM are likelier to report liking their peers: a statistically significant effect of 0.23 points compared to a baseline level of 3.5 (on a scale from 1 to 5) for HSS students. Panel B shows that a generally similar pattern of results persists one year after high school.

Table 12 explores if students experience regret over their high school application choices (e.g., the fact that they ranked STEM tracks highly). The intercept in Column 1 shows that students are mainly satisfied with how they ranked tracks in their high school application—the average satisfaction score is 4.2 (on a five-point scale) for HSS students. The key coefficient indicates this does not meaningfully vary with assignment to STEM. Columns 2-5 further reveal that students, on average, express little desire —if they could go back— to change their choices. Again, this does not vary much with STEM assignment. These results are robust to the use of different bandwidths and samples.

Table 12: Effects on regret over high school application choices one year after high school

	Satisfied with ranking	**If could do over, would:**			
		Make no change	Rank STEM tracks higher	Rank Hum./SS tracks higher	Rank Technical tracks higher
STEM	0.049	0.045	-0.032	-0.018	0.005
	(0.129)	(0.042)	(0.035)	(0.032)	(0.013)
Intercept	4.20	0.80	0.10	0.08	0.02
Std. dev.	0.94	0.38	0.28	0.27	0.14
Cutoffs	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159

The table shows effects on regret over high school application choices. 1.25 point bandwidth. Variables are from the follow-up survey

There is some interesting heterogeneity within these results. One year after high school, low-achieving students who were assigned to STEM are less satisfied with their high school ranking (Table A37), which is consistent with negative updating in response to poor performance on the baccalaureate exam. Also, female students and students who initially preferred HSS come to believe the curriculum was a worse fit for their abilities (Table A35).

Table 13 shows that some dissatisfaction begins to emerge when students reach college. In particular, assignment to STEM has a negative and significant effect on their self-reported enjoyment of the experience and curriculum, along with appreciation of their peers and the instructors, even though STEM continues to have a positive effect on their perceived level of preparedness. Table A41 shows that this decrease in college satisfaction is mainly driven by female students and high-achievers who were assigned to selective high schools. One possible interpretation is that students find the experience of STEM in college more challenging when compared to high school. Another explanation is that college STEM fields are much more male-dominated, possibly more

competitive, the classes larger, and the teaching and evaluation methods are less to the liking of female students and high-achievers, who, on average, had access to a more selective, high-quality high school education.

Table 13: Effects on college satisfaction, curricular fit, and regret one year after high school

	Like the:				**Curriculum is good fit**	**Well prepared**	**Satisfied with ranking**
	Experience	Curriculum	Peers	Instructors			
STEM	-0.443***	-0.227*	-0.398**	-0.352***	0.082	0.490***	0.122
	(0.138)	(0.129)	(0.166)	(0.134)	(0.156)	(0.156)	(0.179)
Intercept	2.20	2.25	2.18	2.31	3.48	2.50	3.72
Std. dev.	1.11	1.09	1.20	1.14	1.33	1.45	1.48
Cutoffs	190	190	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159	1,159	1,159

The table shows effects on college satisfaction and curricular fit from the follow-up survey. Questions were asked only to students who ever attended college. We impute values of 1 for students in the follow-up survey to whom the questions were not asked. 1.25 point bandwidth.

11 Effects on psychological outcomes and political preferences

In this section, we discuss the effect of assignment to STEM on indices of wellbeing, empathy, grit, and trust, on political preferences, and possible mechanisms for these results.

11.1 Outcomes measured at the end of high school

We show that exposure to a STEM curriculum not only changes educational and career preferences, beliefs and paths, but leads to deeper psychological changes. Table 14 (page 31) shows significant impacts on a range of psychological outcomes, for both male and female students. We find overall increases in wellbeing and grit, with the former effect significant for female students and the latter for male students. This is at once reassuring and slightly surprising given that, in our next set of results, we show that STEM students spend more time doing schoolwork.

We then examine the effect on long-term expectations related to work and family (Table 15). Being assigned to STEM has no effect on the amount that students expect to work at age 30, but it leads students to expect to earn a larger share of household income at age 30, but only for male students. The lack of an effect for women could be mechanical and rational: given that IT and engineering are male-dominated and high-earning fields, the expected earnings for women in STEM's spouses may be quite high. Other results suggest that male students expect to have more children by age 30. We average these outcomes into a single measure of "traditionalist expectations", and find a positive overall effect for male students from exposure to STEM.

In Table 16 we examine the effect of STEM on political preferences.[29] In line with our previous

29. We use a standard set General Social Survey questions designed to measure economic and social preferences via questions about attitudes vis-à-vis inequality, safety nets, government intervention, importance of traditions, gender gaps in earnings, divorce, and wage inequalities between spouses.

Table 14: Effects on psychological outcomes

	Wellbeing	Empathy	Grit	Trust
Panel A: All students				
STEM	0.134***	-0.012	0.068*	0.026
	(0.051)	(0.042)	(0.036)	(0.051)
Intercept	-0.10	-0.01	-0.07	-0.05
Std. dev.	0.74	0.70	0.61	0.83
Cutoffs	293	293	293	293
Students	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987
Panel B: Male students				
STEM	0.056	-0.035	0.128**	-0.024
	(0.088)	(0.082)	(0.061)	(0.088)
Intercept	0.04	-0.06	-0.12	0.07
Std. dev.	0.72	0.72	0.59	0.82
Cutoffs	206	206	206	206
Students	1,251	1,251	1,251	1,251
Student-cutoffs	1,396	1,396	1,396	1,396
Panel C: Female students				
STEM	0.143**	-0.013	0.026	0.052
	(0.068)	(0.056)	(0.051)	(0.071)
Intercept	-0.16	0.04	-0.02	-0.13
Std. dev.	0.74	0.68	0.62	0.84
Cutoffs	253	253	253	253
Students	2,254	2,254	2,254	2,254
Student-cutoffs	2,510	2,510	2,510	2,510

The table shows effects on psychological outcomes. 1.25 point bandwidth. Outcomes are averages of standardized versions of answers to component questions. Variables are from the end-of-high-school survey.

results on traditionalist expectations, we find an overall increase in right-wing preferences, which are, interestingly, driven by social rather than economic issues. When we break this down by gender, we find in Panel B that the effect is driven by male students for whom the effect is much larger in magnitude. For male students, there is a statistically significant right shift in economic preferences from STEM. Overall, these results reveal a deep impact of exposure to STEM on both psychological and economic outcomes.

11.2 Mechanisms for end-of-high-school effects on other outcomes

In order to think through some of the mechanisms that could account for the shifts in psychological outlooks and political views, in Table 17 we examine the impact of STEM on time use in high school. Looking at the full sample, we find increases in time spent doing homework, which comes at the expense of time spent reading (not surprising for a STEM student) and social media. Interestingly, the results are distinct for male and female students. Male students spend less time reading, while it is the female STEM students who reduce their time spent on social media. (Also, as shown in the Table A55, the increase in time spent on homework is concentrated among

Table 15: Effects on expectations

	Work amount	Bread-winner	Wealth decile	Number of children	Locale type	Traditionalist expectations
Panel A: All students						
STEM	-0.009	0.091***	0.140	0.048	-0.032	0.098***
	(0.030)	(0.035)	(0.090)	(0.063)	(0.057)	(0.035)
Intercept	2.79	2.15	7.48	1.69	2.81	-0.03
Std. dev.	0.48	0.51	1.44	0.91	0.91	0.52
Cutoffs	293	293	293	293	293	293
Students	3,562	3,562	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987	3,987	3,987
Panel B: Male students						
STEM	0.035	0.150**	0.062	0.173*	-0.076	0.129***
	(0.064)	(0.064)	(0.159)	(0.101)	(0.116)	(0.050)
Intercept	2.72	2.34	7.56	1.65	2.81	0.29
Std. dev.	0.59	0.55	1.46	0.88	0.94	0.44
Cutoffs	206	206	206	206	206	206
Students	1,251	1,251	1,251	1,251	1,251	1,251
Student-cutoffs	1,396	1,396	1,396	1,396	1,396	1,396
Panel C: Female students						
STEM	-0.026	0.014	0.159	0.006	-0.010	0.026
	(0.036)	(0.035)	(0.118)	(0.076)	(0.070)	(0.034)
Intercept	2.83	2.04	7.43	1.68	2.84	-0.22
Std. dev.	0.41	0.41	1.43	0.94	0.89	0.43
Cutoffs	253	253	253	253	253	253
Students	2,254	2,254	2,254	2,254	2,254	2,254
Student-cutoffs	2,510	2,510	2,510	2,510	2,510	2,510

The table shows effects on expectations. 1.25 point bandwidth. Variables are from the end-of-high-school survey. Expectations are for age 30. Work amount is 1 "not at all", 2 "part time", or 3 "full time". Breadwinner is 1 if the students' spouse will contribute most of the household's money, 2 if the partners will contribute equally, and 3 if the student will contribute most of the money. For wealth decile, values are 1 to 10. Number of children is 0, 1, 2, or 3 or more. Locale type is 1 "Rural area/small town", 2 "Medium town", 3 "Outside Romania", and 4 "Big city". Traditionalist expectations is the average of standardized values of the expectations variables, ordered in a traditionalist direction. Specifically, before standardizing and averaging, we reverse the order of Locale type for all students and Work amount and Breadwinner for female students.

low-achieving students.)

Another factor that could explain the rightward shift in male preferences from STEM is a change friendship formation. In particular, in Table 18, we find that STEM assignment leads male students to have fewer good female friends compared to male friends. This is perhaps mechanical, as there are 15 pp fewer females students in STEM tracks, on average.

While this is also true for female students, it does not seem to shift their political preferences toward a more conservative viewpoint. We have some additional results on political outcomes that were measured 1.5 years after high school (Table A53). At that time, being assigned to STEM doesn't affect plans to turn out to vote in important elections. In addition, for males, it has no impact on whether they think that boys are naturally better than girls in math or that climate change is one of the most serious issues that we face. However, for females, being assigned to STEM causes them to less strongly agree that boys are naturally better at math and

Table 16: Effects on political preferences

	Right-wing preferences		
	Any	Economic	Social
Panel A: All students			
STEM	0.058*	0.045	0.070*
	(0.031)	(0.041)	(0.040)
Intercept	-0.04	-0.02	-0.05
Std. dev.	0.46	0.59	0.64
Cutoffs	293	293	293
Students	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987
Panel B: Male students			
STEM	0.145***	0.223***	0.068
	(0.054)	(0.067)	(0.076)
Intercept	-0.02	-0.07	0.03
Std. dev.	0.47	0.60	0.67
Cutoffs	206	206	206
Students	1,251	1,251	1,251
Student-cutoffs	1,396	1,396	1,396
Panel C: Female students			
STEM	0.011	-0.055	0.077
	(0.036)	(0.048)	(0.050)
Intercept	-0.06	-0.01	-0.11
Std. dev.	0.44	0.58	0.62
Cutoffs	253	253	253
Students	2,254	2,254	2,254
Student-cutoffs	2,510	2,510	2,510

The table shows effects on political preferences. 1.25 point bandwidth. Variables are from the end-of-high-school survey. Economic preferences and Social preferences are indices that are ordered such that higher values are more right wing. They are both averages of standardized values of component questions. Any is the average of Economic and Social.

to more strongly agree that climate change is one of the most serious issues we face. Thus, we continue to see a gender-based divergence in the effects.[30]

We are able to revisit these responses 1.5 year after the end of high school (Appendix A9.3). While the responses are noisy, there do not appear to be any significant shifts.

Overall our results suggest that exposure to STEM in high school shifts psychological outlooks, increasing wellbeing and grit, and shifts male students political views rightward and that these impacts are consistent with shifts in patterns of friendships (among boys) and social media use (among girls).

30. In fact, the findings could actually be continued evidence that STEM makes boys more right wing, if the null effects for boys on the math ability and climate change questions reflect defiance to empirical evidence. In other words, boys in HSS may not be provided with any information on gender gaps in math ability or on climate change, while boys in STEM are (namely, that there are no gender gaps in math ability and that climate change is important). Thus, the null effect for boys may actually be the combination of lack of information for HSS-assigned boys and defiance to information for STEM-assigned boys. Meanwhile, the non-zero effects for girls may reflect lack of information for HSS-assigned girls and acceptance of information for STEM-assigned girls.

Table 17: Effects on time use on a typical weekday

	Doing homework	Playing video games	On social media	Reading	Watching TV	With friends	Working for pay	Caring for others	Doing extra-curriculars
Panel A: All students									
STEM	0.248**	-0.096	-0.428***	-0.251***	-0.004	-0.127	0.047	-0.036	0.032
	(0.109)	(0.107)	(0.111)	(0.091)	(0.074)	(0.112)	(0.114)	(0.058)	(0.086)
Intercept	2.44	1.41	3.42	1.42	0.86	2.68	1.63	0.53	0.88
Std. dev.	1.61	1.65	1.69	1.36	1.26	1.76	1.85	1.09	1.36
Cutoffs	293	293	293	293	293	293	293	293	293
Students	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987
Panel B: Male students									
STEM	0.342*	-0.362*	-0.215	-0.472***	-0.050	-0.029	0.114	0.013	0.080
	(0.185)	(0.191)	(0.189)	(0.153)	(0.125)	(0.194)	(0.205)	(0.087)	(0.185)
Intercept	1.86	2.57	2.87	1.17	0.75	2.73	1.67	0.41	1.04
Std. dev.	1.53	1.87	1.69	1.26	1.19	1.86	1.88	0.96	1.47
Cutoffs	206	206	206	206	206	206	206	206	206
Students	1,251	1,251	1,251	1,251	1,251	1,251	1,251	1,251	1,251
Student-cutoffs	1,396	1,396	1,396	1,396	1,396	1,396	1,396	1,396	1,396
Panel C: Female students									
STEM	0.404***	-0.137	-0.437***	-0.103	0.037	-0.235	-0.061	-0.058	0.007
	(0.124)	(0.106)	(0.147)	(0.126)	(0.097)	(0.148)	(0.158)	(0.085)	(0.100)
Intercept	2.66	0.78	3.68	1.59	0.93	2.70	1.62	0.58	0.78
Std. dev.	1.59	1.20	1.64	1.37	1.29	1.70	1.82	1.16	1.27
Cutoffs	253	253	253	253	253	253	253	253	253
Students	2,254	2,254	2,254	2,254	2,254	2,254	2,254	2,254	2,254
Student-cutoffs	2,510	2,510	2,510	2,510	2,510	2,510	2,510	2,510	2,510

The table shows effects on time use. 1.25 point bandwidth. Variables are from the end-of-high-school survey. Values are capped at 6 hours.

12 Curriculum v. peers

One mechanism that is difficult for us to decisively untangle is the effect of a STEM curriculum as compared to the peers that come with STEM. Nonetheless, we have a range of results that corroborate the view that the change in peers is the less consequential of the two. First, while there is a shift in peer composition—notably, fewer female v. male peers and peers who are relatively better in math v. language—our empirical strategy of averaging over STEM-above and HSS-above cutoffs ensures that there is no change (on average) in peer quality as measured by transition score (Appendix A3). Second, we have evidence that peer channels have limited impact on the outcomes we study. Namely, students do not report that peers are a major component of their decision-making (Table A62). In addition, when we estimate the effects of scoring above a within-curriculum cutoff (either STEM above and below or HSS above and below) and thus gaining assignment to a more selective track of the same curriculum, we find null effects (Appendix A12). Finally, we also conduct a cutoff-by-cutoff analysis where we regress cutoff-specific treatment effects on outcomes on first-stage effects on peer attributes. In this analysis, we

Table 18: Effects on friendships

	Good friends	Very close friends	Good female v. male friends
Panel A: All students			
STEM	0.255	-0.096	-1.05***
	(0.369)	(0.177)	(0.257)
Intercept	8.03	3.84	0.77
Std. dev.	5.35	2.75	3.75
Cutoffs	293	293	293
Students	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987
Panel B: Male students			
STEM	-0.158	-0.214	-1.18**
	(0.689)	(0.370)	(0.470)
Intercept	9.49	4.34	-0.93
Std. dev.	5.77	2.92	3.78
Cutoffs	206	206	206
Students	1,251	1,251	1,251
Student-cutoffs	1,396	1,396	1,396
Panel C: Female students			
STEM	0.158	-0.086	-0.663***
	(0.426)	(0.226)	(0.254)
Intercept	7.31	3.54	1.67
Std. dev.	5.03	2.63	3.15
Cutoffs	253	253	253
Students	2,254	2,254	2,254
Student-cutoffs	2,510	2,510	2,510

The table shows effects on friendships. 1.25 point bandwidth. Variables are from the end-of-high-school survey. Good friends is capped at 20, and very close friends is capped at 10. Good female v. male friends is the difference between good female and good male friends. It is restricted to -10 to 10.

find that the effects on peer attributes have little explanatory power for the effects on outcomes (Appendix A13). Thus, overall, it seems reasonable to conclude that the effects of STEM v. HSS tracks the we estimated in prior sections are mostly driven by changes in curriculum, not peers.

13 Conclusion

In the last several decades, there has been an increasing emphasis on STEM education both in general and specifically in schools. A STEM education can not only yield substantial private returns (Arcidiacono, Hotz, and Kang (2012)) but also benefits innovation and growth in the macro economy (Aghion et al. (2009), Peri, Shih, and Sparber (2015)). In this paper, we have focused both on the *how* of increasing STEM education and also the mechanisms and possible tradeoffs in emphasizing STEM over a traditional humanities education, which was lauded in a previous generation as a pathway to a prosperous and engaged civil society (Arendt (1961)).

Our key finding on how to increase STEM education is that students retain significant malleability even as high school students (which is consistent with the mindset strand of the psy-

chology literature; see for example Blackwell, Trzesniewski, and Dweck (2007) and Yeager et al. (2019)). Significant exposure to STEM not only increases pursuit of a STEM education, but also shifts self-perceived strengths and interests in the same direction. It is striking that after four years of STEM students have shifted their personality profiles and suggested career trajectories in the O*Net profile. At the level of O*Net and our surveys and also choice of college major and expectations of future labor market trajectories, it turns out that there is significant malleability in high school. While there has rightly been considerable focus on early childhood education (Heckman (2006), Heckman et al. (2010), Del Boca, Flinn, and Wiswall (2014)), high school is a pivotal moment in education and career choice. So in that sense, we believe that our results possibly reflect a lasting shift in students' eventual trajectories toward STEM.

At the same time, the STEM pathway comes with risks and tradeoffs (see also Deming and Noray (2020)). The risks are twofold as identified in our results. First, low baseline achievements students are less likely to succeed in STEM, and failure in high school, whatever the major, carries significant long-term harms. Second, we find a consistent thread of evidence suggesting that as they progress from high school to college girls are less satisfied with the choice of a STEM track. The latter is of course highly consistent with gender gaps in STEM in college graduation rates and subsequent careers.

The larger tradeoff we uncover harks back to Nussbaum (2010)'s case for the importance of a humanities education. STEM focused students, specifically boys, are more economically and socially conservative, with the interesting silver lining that STEM-focused girls in fact seem to reduce their exposure to social media (plausibly simply from the reality of time constraints in a STEM education) and emerge with a greater belief in their abilities.

While our results delineate a possible pathway to increasing STEM education, they also highlight some consequences both expected and unexpected that strike a cautionary note.

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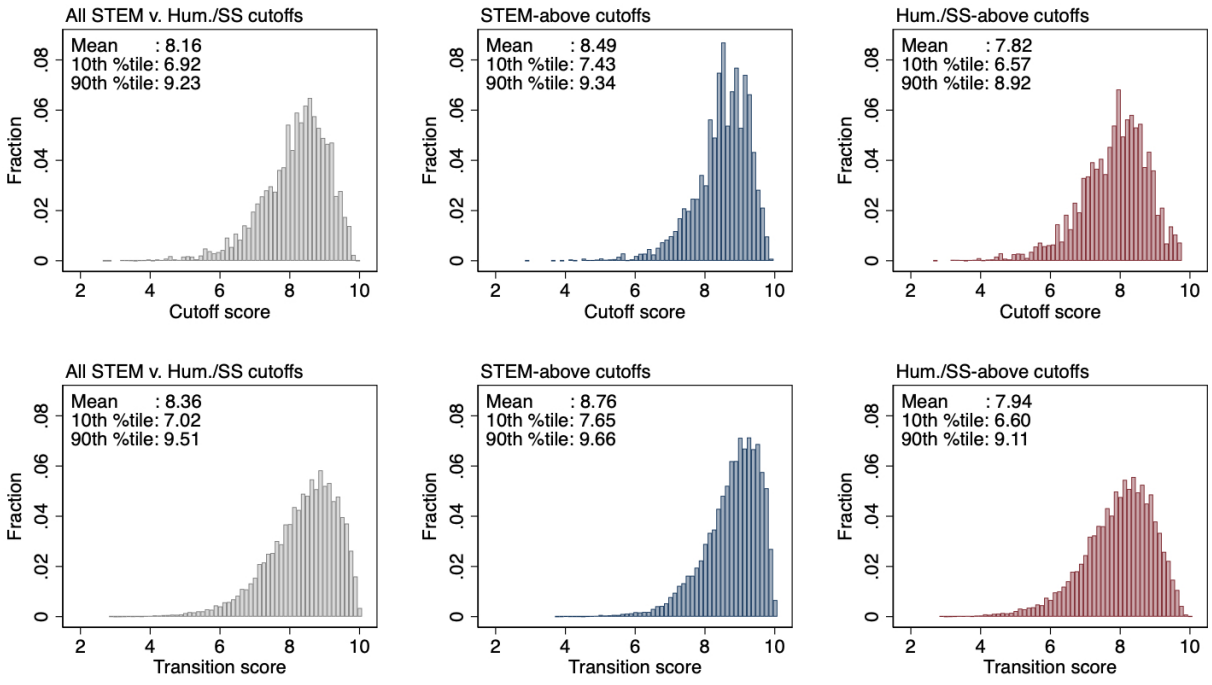
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A1 Characterizing students at STEM v. HSS cutoffs

In this Appendix, we investigate the characteristics of students who are at the assignment cutoff between a STEM and HSS track. In Figure A1, we show the distribution of cutoff scores between these two categories of tracks, and then show separately the distribution of cutoffs when STEM is the track above cutoff ("STEM-above") and when instead this is Humanities or Social Studies ("HSS-above"). We see that the distributions span almost the full range of scores and include a range of cutoffs from less selective to highly selective. While the full distribution of cutoffs is somewhat skewed to the right, the STEM-above cutoffs are more notably right-skewed toward selectivity compared to the HSS-above cutoffs, although both continue to span almost the full range of scores.

In the lower half of Figure A1, we show the distribution of transition scores for the same types of cutoffs. For the full sample, we see that although most students at a STEM-HSS cutoff are in the upper half of the range of transition scores, hence, with above average baseline achievement, there is a meaningful left tail of students with lower baseline achievement. While both distributions span a similar range, selectivity is more pronounced among students at a STEM-above track compared to those at a HSS-above track, with a right-skew in transition scores.

Figure A1: The distribution of cutoff scores and transition scores in the RD sample



The plots in the top row present histograms for the distribution of cutoff scores in the RD sample, weighted by the number of students at each cutoff. The plots in the bottom row are for the distribution of student transition scores in the RD sample. The figure uses administrative data for the 2015-2017 and 2019 cohorts.

We examine the relationship between our research sample and the full sample of students in Tables A1-A3. In Table A1, we see that the distribution of transition scores in our RD sample reflects higher baseline ability than the full sample, with an average transition score of 8.36 compared to 7.57, but is comparable to the distribution for the top 70 percent of students in the full sample. Again, the STEM-above sample has higher baseline ability than the HSS-above sample,

with an average transition score of 8.76 compared to 7.94 and notably higher math exam scores, although also higher language scores and middle school GPAs.

Table A1: Comparing the RD sample with the full administrative data

	Transition score								**Female**		**N**
	Overall score		Math exam score		Lang. exam score		Grades 5-8 GPA				
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
All students	7.57	1.61	6.79	2.19	7.57	1.80	8.90	0.86	0.50	0.50	207,632
Top 70%	8.36	0.96	7.78	1.52	8.40	1.04	9.27	0.58	0.53	0.50	152,636
RD sample	8.36	1.01	7.76	1.57	8.42	1.10	9.27	0.57	0.56	0.50	73,470
Prefer STEM	8.76	0.82	8.39	1.29	8.74	0.93	9.44	0.49	0.55	0.50	37,376
Prefer Hum./SS	7.94	1.01	7.11	1.56	8.10	1.16	9.09	0.60	0.58	0.49	36,094

The table presents summary statistics for different samples of students. "All students" is the entire administrative data (all students for whom we have rank-ordered lists). "Top 70%" is students in the administrative data with transition scores that are in the top 70 percent of the yearly national distribution. "Prefer STEM" and "Prefer HSS" are, respectively, the portions of the RD sample for STEM-above and HSS-above cutoffs. For "All students" and "Top 70%", N is the number of students. For the remaining rows, it is the number of student-cutoff combinations. The table uses administrative data for the 2015-2017 and 2019 cohorts.

In Table A2, we see that it is common for students to rank both STEM and HSS tracks (of the full sample, 75 percent rank both among their choices and 50 percent rank both among their top 5 choices), although this more pronounced in the top-70 percent of the sample (with 80 percent ranking both among their choices). Interestingly, students who are stronger in language are even more likely to rank both STEM and HSS among their top choices (87 percent among all choices, 63 percent in the top 5).

Table A2: The percent of students who rank both STEM and HSS

	At all	**In top 10**	**In top 5**
All students	75	64	50
Top 70%:			
All	80	69	54
Stronger in math	77	64	49
Stronger in language	87	78	63
Male	77	64	50
Female	84	73	58

The table displays the percent of students who rank both a STEM and a HSS track either (i) at all, (ii) in their top 10 choices, or (iii) in their top 5 choices. "All students" is the entire administrative data (all students for whom we have rank-ordered lists). "Top 70%" is students in the administrative data with transition scores that are in the top 70 percent of the yearly national distribution. "Stronger in math", "Stronger in language", "Male", and "Female" are subsets of "Top 70%". The table uses administrative data for the 2015-2017 and 2019 cohorts.

In Table A3, we unpack this for STEM and HSS rankings separately. Students who are stronger in math are somewhat more skewed toward STEM tracks than students who stronger in language. Among the former, 98 percent rank STEM tracks in their top-5 and 54 percent rank HSS in their top 5, compared to the latter group where these percentages are 85 and 77 respectively.

Overall, these results suggest that it is common for students to rank both STEM and HSS tracks, especially among those in the top 70 percent of the baseline achievement distribution.

Table A3: Summary statistics on ranking STEM and HSS

	STEM				Hum./SS			
	% rank at all	% rank in top 10	% rank in top 5	Minimum rank	% rank at all	% rank in top 10	% rank in top 5	Minimum rank
All students	95	92	86	3.1	77	68	58	6.8
Top 70%:								
All	98	95	90	2.6	83	73	63	6.2
Stronger in math	98	97	94	2.1	78	67	54	7.4
Stronger in language	96	92	85	3.5	90	85	77	4.3
Male	98	96	93	2.2	78	67	55	7.3
Female	97	93	88	3.0	87	80	69	5.3

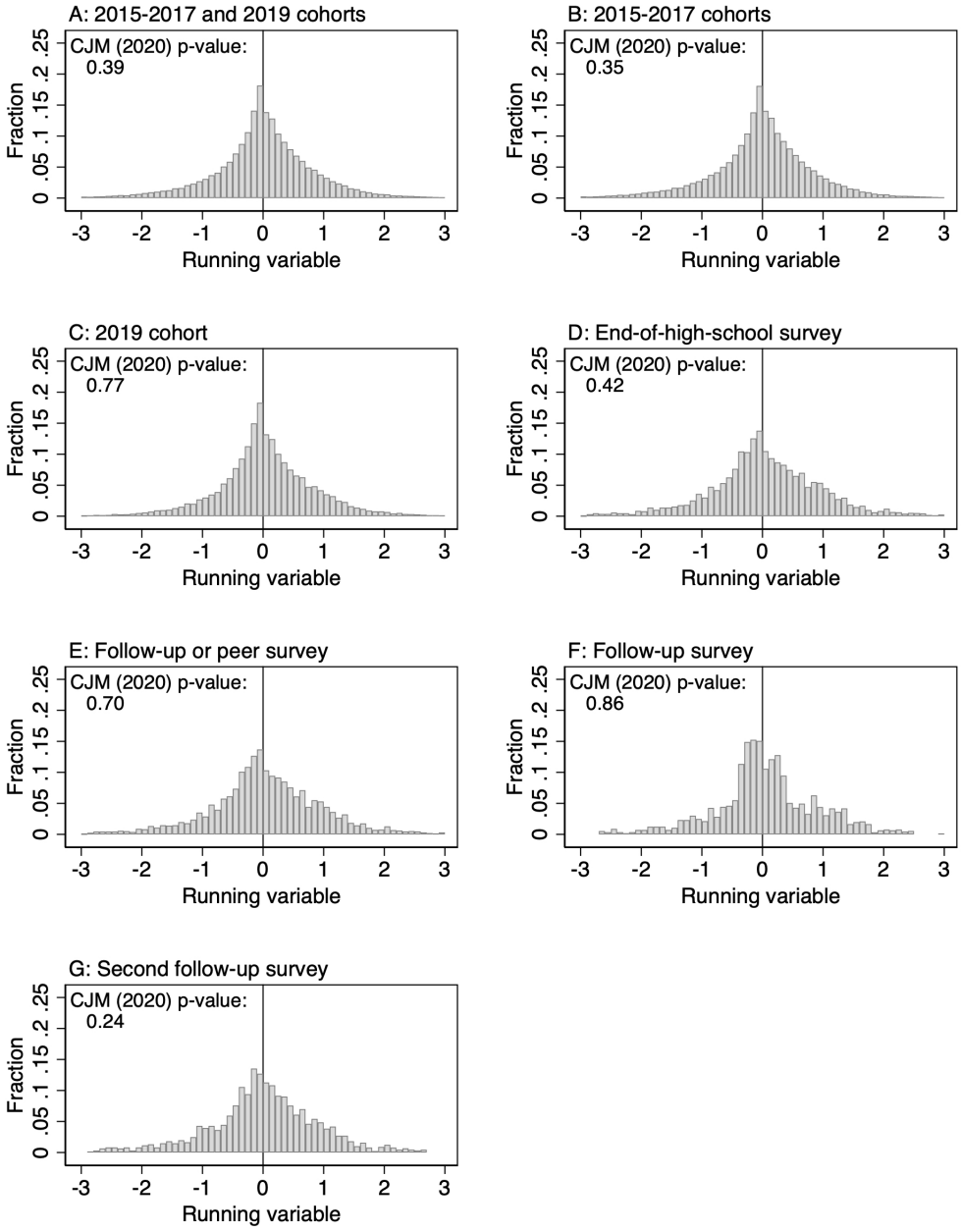
The table provides summary statistics on students' ranking behavior with respect to STEM and HSS tracks. "Minimum rank" is the mean over the sample of the lowest (most favorable) rank that a student gives to a track with a given curriculum. If a student doesn't rank any track with the curriculum, we impute a value of 14, which is the median total number of tracks ranked. The table uses administrative data for the 2015-2017 and 2019 cohorts.

A2 Manipulation, balance, and selection

In this Appendix we present manipulation and balance checks for our regression discontinuity design.

Figure A2 depicts the Cattaneo, Jansson, and Ma (2020) manipulation checks with respect to the transition score, which is our running variable, for our administrative and survey research samples. The figures normalize the cutoffs at 0. The seven panels show a relatively smooth distribution at the cutoff. While there are a few jumps visible, the p-values associated with these indicate that they are not statistically significant at standard levels.

Figure A2: Histograms of the running variable by sample



The figure shows histograms of the running variable for the paper's various samples. The CJM (2020) p-value is the p-value from the Cattaneo, Jansson, and Ma (2020) discontinuity-in-density test of manipulation of the running variable.

In Table A4, we unpack this by examining covariate differences at the cutoff, specifically the transition score and its components and the proportion female. Note that since we are taking an average of STEM-above and HSS-above tracks, the differences for an above-the-cutoff indicator, a prefers-STEM indicator, and the overall score are zero by construction. Looking at the transition score and components and at mother's and father's education, we see no statistically significant differences across our samples. For our end-of-high-school and follow-up surveys we find female students are somewhat underrepresented in STEM tracks (a 6-7 percentage point difference in Pan-

els D and E, significant at the 10 percent level). Taken jointly, we can reject covariate differences at standard levels. As a robustness check, we include student-level covariates in our specification, which does not meaningfully affect results.

Finally in Table A5 , we examine selection from the administrative data into being a survey respondent in our four survey samples. There are few meaningful or statistically significant differences. There is a slight overrepresentation of males in the end-of high-school and follow-up surveys, and a slight overrepresentation of low-cutoff-score respondents in our second-follow-up survey. The differences are not jointly significant at standard levels.

Overall, these results suggest that there is no evidence of manipulation of transition scores with respect to assignment cutoffs, that there is covariate balance at the cutoffs, and that there is minimal evidence of selection into our survey samples.

Table A4: Balance and summary statistics for the RD samples

	Above the cutoff	**Prefer STEM**	**Transition score**				**Female**	**Years of schooling**	
			Overall score	Math exam score	Language exam score	Grades 5-8 GPA		Father	Mother
Panel A: 2015-2017 and 2019 cohorts									
STEM	0.000	0.000	0.000	-0.005	0.000	0.005	-0.010	-	-
	(0.000)	(0.000)	(0.000)	(0.008)	(0.008)	(0.005)	(0.007)	-	-
Intercept	0.50	0.50	8.16	7.49	8.23	9.16	0.52	-	-
Mean	0.66	0.51	8.36	7.76	8.42	9.27	0.56	-	-
Std. dev.	0.47	0.50	1.01	1.57	1.10	0.57	0.50	-	-
Cutoffs	1,904	1,904	1,904	1,904	1,904	1,904	1,904	-	-
Students	62,301	62,301	62,301	62,301	62,301	62,301	62,301	-	-
Student-cutoffs	73,470	73,470	73,470	73,470	73,470	73,470	73,470	-	-
Panel B: 2015-2017 cohorts									
STEM	0.000	0.000	0.000	-0.000	-0.002	0.003	-0.007	-	-
	(0.000)	(0.000)	(0.000)	(0.009)	(0.009)	(0.006)	(0.009)	-	-
Intercept	0.50	0.50	8.21	7.67	8.19	9.13	0.52	-	-
Mean	0.66	0.52	8.42	7.94	8.40	9.24	0.56	-	-
Std. dev.	0.47	0.50	1.01	1.54	1.09	0.59	0.50	-	-
Cutoffs	1,411	1,411	1,411	1,411	1,411	1,411	1,411	-	-
Students	46,789	46,789	46,789	46,789	46,789	46,789	46,789	-	-
Student-cutoffs	55,221	55,221	55,221	55,221	55,221	55,221	55,221	-	-
Panel C: 2019 cohort									
STEM	0.000	0.000	0.000	-0.011	0.002	0.006	-0.021	-	-
	(0.000)	(0.000)	(0.000)	(0.016)	(0.016)	(0.010)	(0.015)	-	-
Intercept	0.50	0.50	7.98	6.95	8.37	9.26	0.55	-	-
Mean	0.64	0.48	8.16	7.22	8.49	9.33	0.57	-	-
Std. dev.	0.48	0.50	0.99	1.50	1.11	0.52	0.49	-	-
Cutoffs	493	493	493	493	493	493	493	-	-
Students	15,512	15,512	15,512	15,512	15,512	15,512	15,512	-	-
Student-cutoffs	18,249	18,249	18,249	18,249	18,249	18,249	18,249	-	-
Panel D: End-of-high-school survey									
STEM	0.000	0.000	0.000	-0.016	0.007	-0.007	-0.067*	-0.089	-0.088
	(0.000)	(0.000)	(0.000)	(0.039)	(0.038)	(0.021)	(0.034)	(0.116)	(0.117)
Intercept	0.50	0.50	7.88	6.76	8.31	9.27	0.64	13.0	13.5
Mean	0.65	0.48	8.08	7.09	8.45	9.34	0.64	13.2	13.5
Std. dev.	0.48	0.50	1.00	1.52	1.11	0.49	0.48	1.94	1.73
Cutoffs	293	293	293	293	293	293	293	293	293
Students	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987
Panel E: Follow-up or peer survey									
STEM	0.000	0.000	0.000	-0.021	0.009	-0.014	-0.063*	-0.082	-0.095
	(0.000)	(0.000)	(0.000)	(0.039)	(0.036)	(0.023)	(0.037)	(0.135)	(0.130)
Intercept	0.50	0.50	7.90	6.78	8.34	9.28	0.64	13.1	13.5
Mean	0.65	0.48	8.10	7.10	8.47	9.34	0.64	13.2	13.5
Std. dev.	0.48	0.50	1.00	1.52	1.09	0.50	0.48	1.92	1.73
Cutoffs	280	280	280	280	280	280	280	280	280
Students	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978
Student-cutoffs	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327
Panel F: Follow-up survey									
STEM	0.000	0.000	0.000	0.021	0.001	-0.043	-0.026	-0.198	-0.116
	(0.000)	(0.000)	(0.000)	(0.067)	(0.061)	(0.039)	(0.061)	(0.270)	(0.213)
Intercept	0.50	0.50	7.98	6.88	8.41	9.32	0.66	13.2	13.5
Mean	0.66	0.51	8.19	7.25	8.54	9.38	0.67	13.1	13.5
Std. dev.	0.47	0.50	0.93	1.47	1.00	0.46	0.47	1.95	1.75
Cutoffs	190	190	190	190	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159
Panel G: Second follow-up survey									
STEM	0.000	0.000	0.000	0.030	-0.012	0.001	-0.061	0.206	-0.071
	(0.000)	(0.000)	(0.000)	(0.067)	(0.056)	(0.042)	(0.063)	(0.258)	(0.216)
Intercept	0.50	0.50	7.93	6.81	8.35	9.30	0.63	12.7	13.2
Mean	0.66	0.48	8.14	7.17	8.51	9.36	0.64	13.1	13.4
Std. dev.	0.47	0.50	0.95	1.49	1.02	0.48	0.48	1.96	1.75
Cutoffs	198	198	198	198	198	198	198	198	198
Students	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199

The table . . . 1.25 point bandwidth. Years of schooling is taken from the end-of-high-school survey. Using all variables, p-values for a test of joint significance are 0.353, 0.737, 0.585, 0.380, 0.157, 0.962, and 0.969, respectively. Excluding the variables for which coefficients are mechanically zero, p-values are 0.362, 0.846, 0.333, 0.146, 0.045, 0.888, and 0.900, respectively. Mean and Std. dev. are the mean and standard deviation of the outcome among students within the RD bandwidth.

Table A5: Selection into being a survey respondent

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: End-of-high-school survey									
STEM	0.010	0.005	0.015	0.007	0.009	0.039**	-0.007	0.020	0.006
	(0.015)	(0.015)	(0.024)	(0.016)	(0.021)	(0.018)	(0.019)	(0.025)	(0.016)
Intercept	0.19	0.18	0.21	0.18	0.20	0.15	0.22	0.20	0.17
Mean	0.22	0.22	0.22	0.21	0.23	0.19	0.25	0.24	0.20
Panel B: Follow-up or peer survey									
STEM	0.008	0.005	0.010	0.002	0.009	0.030*	-0.005	0.022	0.001
	(0.012)	(0.013)	(0.019)	(0.015)	(0.018)	(0.016)	(0.017)	(0.020)	(0.014)
Intercept	0.16	0.15	0.18	0.15	0.17	0.13	0.19	0.17	0.15
Mean	0.18	0.18	0.19	0.18	0.19	0.15	0.21	0.20	0.17
Panel C: Follow-up survey									
STEM	0.002	0.006	-0.003	0.007	-0.003	0.010	-0.006	0.010	-0.003
	(0.008)	(0.009)	(0.011)	(0.010)	(0.012)	(0.010)	(0.012)	(0.012)	(0.010)
Intercept	0.07	0.07	0.08	0.06	0.08	0.05	0.09	0.07	0.07
Mean	0.07	0.07	0.06	0.07	0.07	0.05	0.08	0.07	0.07
Panel D: Second follow-up survey									
STEM	0.008	0.007	0.008	0.006	0.010	0.014	0.006	0.021*	-0.004
	(0.007)	(0.008)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.008)
Intercept	0.06	0.05	0.06	0.06	0.06	0.05	0.07	0.06	0.06
Mean	0.07	0.07	0.07	0.07	0.07	0.06	0.08	0.08	0.06
Cutoffs	493	255	238	424	414	422	442	280	213
Students	15,512	8,850	9,399	7,936	7,519	6,570	8,887	8,100	8,063
Student-cutoffs	18,249	8,850	9,399	9,320	8,837	7,773	10,399	8,703	9,546

The table . . . 1.25 point bandwidth. Sample is the 2019 cohort and is the same for all panels; thus, we present it in a single set of rows at the bottom of the table.

A3 Additional results for effects on attributes of assigned tracks

Table A6: Effects on attributes of students' assigned tracks by sample

	Average		Share Female
	Transition score	Math v. language transition exam score	
Panel A: 2015-2017 and 2019 cohorts			
STEM	-0.007	0.357***	-0.150***
	(0.007)	(0.010)	(0.004)
Intercept	8.33	-0.89	0.66
Cutoffs	1,904	1,904	1,904
Students	62,301	62,301	62,301
Student-cutoffs	73,470	73,470	73,470
Panel B: 2015-2017 cohorts			
STEM	-0.011	0.351***	-0.151***
	(0.008)	(0.011)	(0.005)
Intercept	8.40	-0.67	0.66
Cutoffs	1,411	1,411	1,411
Students	46,789	46,789	46,789
Student-cutoffs	55,221	55,221	55,221
Panel C: 2019 cohort			
STEM	0.009	0.387***	-0.149***
	(0.015)	(0.019)	(0.008)
Intercept	8.14	-1.56	0.66
Cutoffs	493	493	493
Students	15,512	15,512	15,512
Student-cutoffs	18,249	18,249	18,249
Panel D: End-of-high-school survey			
STEM	0.012	0.405***	-0.132***
	(0.027)	(0.030)	(0.013)
Intercept	8.08	-1.65	0.65
Cutoffs	293	293	293
Students	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987
Panel E: Follow-up or peer survey			
STEM	0.014	0.410***	-0.129***
	(0.028)	(0.031)	(0.014)
Intercept	8.10	-1.65	0.65
Cutoffs	280	280	280
Students	2,978	2,978	2,978
Student-cutoffs	3,327	3,327	3,327
Panel F: Follow-up survey			
STEM	0.013	0.437***	-0.121***
	(0.038)	(0.038)	(0.018)
Intercept	8.16	-1.65	0.65
Cutoffs	190	190	190
Students	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159
Panel G: Second follow-up survey			
STEM	-0.017	0.415***	-0.134***
	(0.034)	(0.045)	(0.021)
Intercept	8.14	-1.67	0.65
Cutoffs	198	198	198
Students	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199

The table is the same as Table 2 but for the listed samples.

- Results are similar for different samples, suggesting again that the surveys are representative.

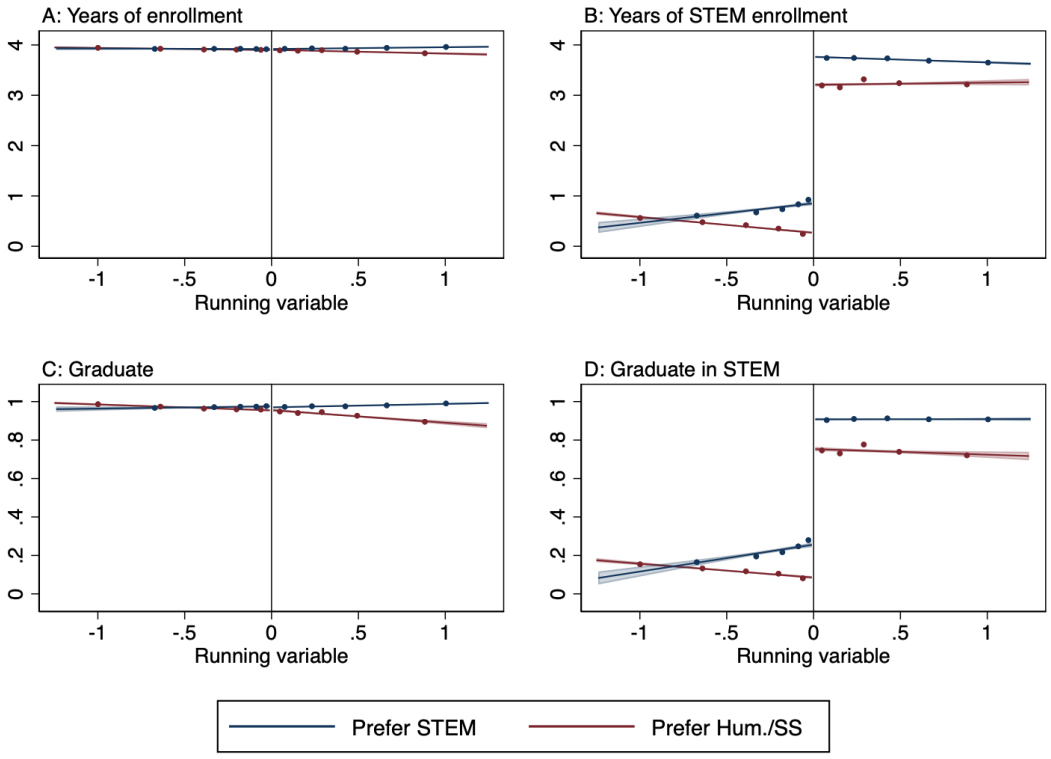
A4 Additional results for effects on high school outcomes

Table A7: Robustness for effects on enrollment and graduation

	Main	**Alternative bandwidths**				**Adding covariates**
		0.75	1.00	1.50	1.75	
Panel A: Years of enrollment						
STEM	0.002	0.001	0.001	0.001	-0.000	0.002
	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
Panel B: Years of STEM enrollment						
STEM	3.08***	3.04***	3.06***	3.09***	3.10***	3.08***
	(0.023)	(0.025)	(0.024)	(0.022)	(0.021)	(0.023)
Panel C: Graduate						
STEM	-0.003	-0.005	-0.004	-0.004	-0.004	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel D: Graduate in STEM						
STEM	0.694***	0.683***	0.688***	0.697***	0.701***	0.693***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Cutoffs	1,411	1,320	1,371	1,442	1,466	1,411
Students	46,789	37,345	42,931	49,515	51,335	46,789
Student-cutoffs	55,221	44,749	51,050	58,122	60,052	55,221

The table shows robustness for some of the results in Table 3. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score and an indicator for female. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A3: Graphical depiction of effects on enrollment and graduation



The figure plots RD treatment effects for the outcomes in Table A7.

Table A8: Effects on enrollment and graduation with no restriction on outcome timing

	Years of enrollment				Graduate			
	All	STEM	Hum./SS	Technical	All	STEM	Hum./SS	Technical
STEM	0.004	3.08***	-3.09***	0.014**	-0.001	0.697***	-0.704***	0.006***
	(0.007)	(0.023)	(0.023)	(0.006)	(0.003)	(0.007)	(0.008)	(0.002)
Intercept	3.91	0.50	3.37	0.05	0.97	0.16	0.80	0.01
Std. dev.	0.41	1.89	1.88	0.38	0.17	0.50	0.49	0.12
Cutoffs	1,411	1,411	1,411	1,411	1,411	1,411	1,411	1,411
Students	46,789	46,789	46,789	46,789	46,789	46,789	46,789	46,789
Student-cutoffs	55,221	55,221	55,221	55,221	55,221	55,221	55,221	55,221

The table is analogous to Table 3 but with no restriction on when outcomes are measured.

Table A9: Heterogeneity for effects on enrollment and graduation

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Years of enrollment									
STEM	0.002	0.000	0.003	0.010	-0.017	0.008	0.000	0.007	-0.000
	(0.007)	(0.008)	(0.008)	(0.009)	(0.011)	(0.010)	(0.009)	(0.016)	(0.008)
Intercept	3.91	3.92	3.90	3.91	3.91	3.90	3.91	3.87	3.93
Panel B: Years of STEM enrollment									
STEM	3.08***	3.01***	3.14***	3.00***	3.22***	2.87***	3.26***	3.25***	3.02***
	(0.023)	(0.030)	(0.027)	(0.028)	(0.031)	(0.033)	(0.025)	(0.038)	(0.028)
Intercept	0.50	0.68	0.32	0.66	0.22	0.68	0.34	0.13	0.66
Panel C: Graduate									
STEM	-0.003	-0.006*	0.001	-0.001	-0.007	-0.002	-0.001	-0.011	-0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.008)	(0.003)
Intercept	0.96	0.97	0.95	0.97	0.96	0.96	0.96	0.94	0.98
Panel D: Graduate in STEM									
STEM	0.694***	0.673***	0.714***	0.674***	0.732***	0.630***	0.751***	0.732***	0.683***
	(0.007)	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)	(0.009)	(0.013)	(0.009)
Intercept	0.16	0.22	0.10	0.21	0.07	0.21	0.11	0.04	0.21
Cutoffs	1,411	718	693	1,240	1,165	1,228	1,242	719	692
Students	46,789	28,526	26,695	30,091	16,543	20,141	26,521	17,374	31,116
Student-cutoffs	55,221	28,526	26,695	35,757	19,223	24,127	30,896	18,501	36,720

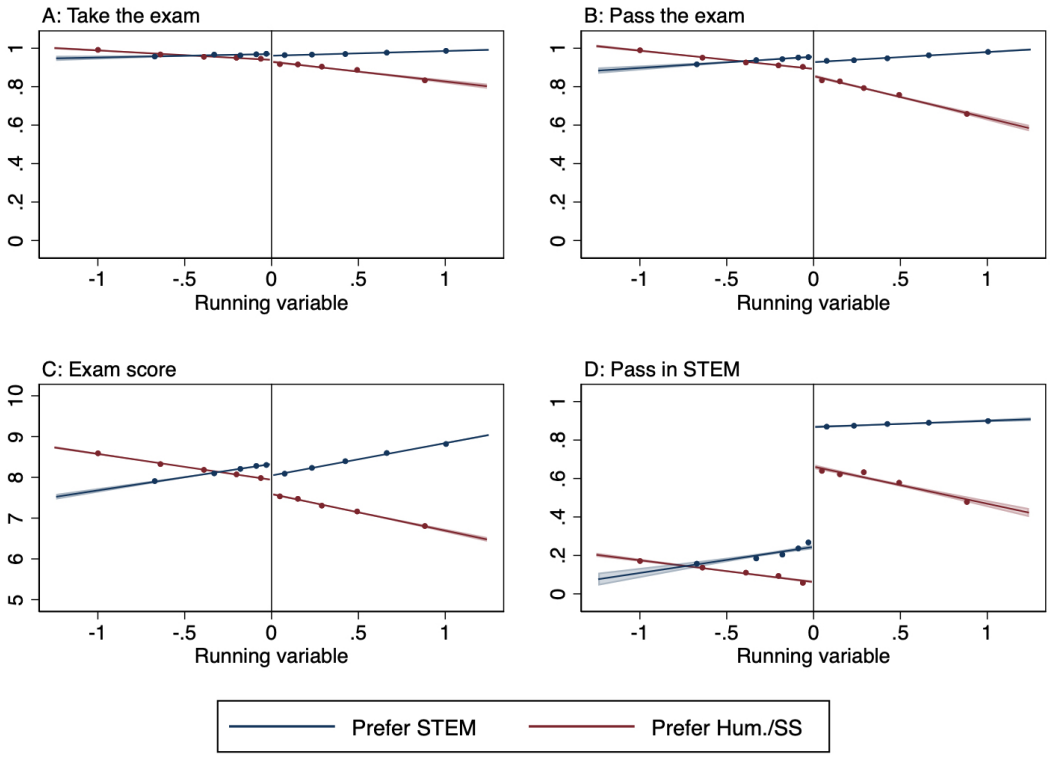
The table shows heterogeneity for some of the results in Table 3. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A10: Robustness for effects on baccalaureate performance

	Main	**Alternative bandwidths**				**Adding covariates**
		0.75	1.00	1.50	1.75	
Panel A: Take the exam						
STEM	-0.011***	-0.013***	-0.011***	-0.012***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Cutoffs	1,904	1,779	1,848	1,946	1,982	1,904
Students	62,301	49,505	57,046	65,933	68,306	62,301
Student-cutoffs	73,470	59,375	67,804	77,330	79,842	73,470
Panel B: Pass the exam						
STEM	-0.036***	-0.038***	-0.037***	-0.039***	-0.040***	-0.036***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Cutoffs	1,904	1,779	1,848	1,946	1,982	1,904
Students	62,301	49,505	57,046	65,933	68,306	62,301
Student-cutoffs	73,470	59,375	67,804	77,330	79,842	73,470
Panel C: Exam score						
STEM	-0.351***	-0.355***	-0.351***	-0.355***	-0.360***	-0.351***
	(0.015)	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)
Cutoffs	1,855	1,731	1,797	1,897	1,938	1,855
Students	59,127	47,059	54,153	62,523	64,735	59,127
Student-cutoffs	69,938	56,635	64,577	73,545	75,887	69,938
Panel D: Pass in STEM						
STEM	0.642***	0.632***	0.638***	0.643***	0.645***	0.641***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Cutoffs	1,411	1,320	1,371	1,442	1,466	1,411
Students	46,789	37,345	42,931	49,515	51,335	46,789
Student-cutoffs	55,221	44,749	51,050	58,122	60,052	55,221

The table shows robustness for some of the results in Table 4. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score and an indicator for female.

Figure A4: Graphical depiction of effects on baccalaureate performance



The figure plots RD treatment effects for the outcomes in Table A10.

Table A11: Effects on baccalaureate performance with no restriction on outcome timing

	Take the exam	**Pass the exam**	**Exam score**	**Pass in**		
				STEM	Hum./SS	Technical
STEM	-0.010***	-0.028***	-0.345***	0.654***	-0.689***	0.005***
	(0.003)	(0.004)	(0.015)	(0.008)	(0.008)	(0.002)
Intercept	0.96	0.93	8.09	0.14	0.78	0.01
Std. dev.	0.21	0.27	1.19	0.50	0.49	0.10
Cutoffs	1,904	1,904	1,856	1,411	1,411	1,411
Students	62,301	62,301	59,302	46,789	46,789	46,789
Student-cutoffs	73,470	73,470	70,141	55,221	55,221	55,221

The table is analogous to Table 4 but with no restriction on when outcomes are measured.

Table A12: Effects on baccalaureate performance by sample

	All students			Low cutoff score			High cutoff score		
	Take the exam	Pass the exam	Exam score	Take the exam	Pass the exam	Exam score	Take the exam	Pass the exam	Exam score
Panel A: 2015-2017 and 2019 cohorts									
STEM	-0.011***	-0.036***	-0.351***	-0.035***	-0.111***	-0.502***	-0.001	-0.008**	-0.302***
	(0.003)	(0.004)	(0.015)	(0.007)	(0.010)	(0.032)	(0.003)	(0.003)	(0.016)
Intercept	0.95	0.92	8.08	0.92	0.86	7.45	0.98	0.97	8.44
Cutoffs	1,904	1,904	1,855	999	999	955	905	905	900
Students	62,301	62,301	59,127	25,474	25,474	23,153	39,179	39,179	38,257
Student-cutoffs	73,470	73,470	69,938	27,204	27,204	24,751	46,266	46,266	45,187
Panel B: 2015-2017 cohorts									
STEM	-0.012***	-0.039***	-0.341***	-0.047***	-0.135***	-0.507***	-0.001	-0.008**	-0.298***
	(0.003)	(0.005)	(0.017)	(0.010)	(0.013)	(0.040)	(0.003)	(0.004)	(0.018)
Intercept	0.95	0.91	8.06	0.91	0.84	7.34	0.97	0.97	8.41
Cutoffs	1,411	1,411	1,370	719	719	682	692	692	688
Students	46,789	46,789	44,230	17,374	17,374	15,540	31,116	31,116	30,339
Student-cutoffs	55,221	55,221	52,369	18,501	18,501	16,561	36,720	36,720	35,808
Panel C: 2019 cohort									
STEM	-0.007	-0.030***	-0.390***	-0.013	-0.068***	-0.503***	-0.002	-0.005	-0.318***
	(0.005)	(0.007)	(0.028)	(0.010)	(0.015)	(0.051)	(0.005)	(0.005)	(0.036)
Intercept	0.97	0.94	8.14	0.95	0.92	7.69	0.99	0.98	8.54
Cutoffs	493	493	485	280	280	273	213	213	212
Students	15,512	15,512	14,897	8,100	8,100	7,613	8,063	8,063	7,918
Student-cutoffs	18,249	18,249	17,569	8,703	8,703	8,190	9,546	9,546	9,379
Panel D: End-of-high-school survey									
STEM	0.001	-0.023**	-0.455***	-0.003	-0.050**	-0.479***	0.006	0.006	-0.376***
	(0.006)	(0.010)	(0.057)	(0.015)	(0.020)	(0.107)	(0.005)	(0.009)	(0.083)
Intercept	0.99	0.96	8.27	0.98	0.95	7.81	0.99	0.99	8.71
Cutoffs	293	293	289	173	173	169	120	120	120
Students	3,562	3,562	3,508	2,011	2,011	1,959	1,683	1,683	1,681
Student-cutoffs	3,987	3,987	3,929	2,093	2,093	2,038	1,894	1,894	1,891
Panel E: Follow-up or peer survey									
STEM	-0.009	-0.027**	-0.438***	-0.023	-0.065***	-0.435***	0.002	0.008	-0.353***
	(0.006)	(0.012)	(0.061)	(0.014)	(0.023)	(0.113)	(0.002)	(0.008)	(0.086)
Intercept	0.99	0.97	8.28	1.00	0.97	7.80	1.00	0.99	8.71
Cutoffs	280	280	278	161	161	159	119	119	119
Students	2,978	2,978	2,934	1,637	1,637	1,594	1,445	1,445	1,444
Student-cutoffs	3,327	3,327	3,282	1,703	1,703	1,659	1,624	1,624	1,623
Panel F: Follow-up survey									
STEM	-0.004	-0.015	-0.551***	-0.007	-0.061*	-0.678***	0.000	0.023	-0.499***
	(0.009)	(0.019)	(0.096)	(0.015)	(0.033)	(0.172)	(0.000)	(0.019)	(0.148)
Intercept	0.99	0.99	8.45	0.99	0.99	8.04	1.00	0.99	8.86
Cutoffs	190	190	187	104	104	101	86	86	86
Students	1,046	1,046	1,036	525	525	515	545	545	545
Student-cutoffs	1,159	1,159	1,149	547	547	537	612	612	612
Panel G: Second follow-up survey									
STEM	0.010	-0.014	-0.358***	0.005	-0.075*	-0.134	0.013	0.022	-0.391***
	(0.008)	(0.021)	(0.107)	(0.007)	(0.039)	(0.165)	(0.012)	(0.014)	(0.143)
Intercept	0.99	0.97	8.25	0.99	0.98	7.66	0.98	0.98	8.75
Cutoffs	198	198	194	107	107	103	91	91	91
Students	1,089	1,089	1,076	606	606	594	515	515	514
Student-cutoffs	1,199	1,199	1,185	618	618	606	581	581	579

The table is the same as the first three columns of Table 4 but for the listed samples. A low (high) cutoff score is less than or equal to (greater than) 8.

Table A13: Effects on baccalaureate performance for the survey samples

	Follow-up or peer		**Follow-up**				
	Take the exam	Pass the exam	Take the exam	Pass the exam	Exam score	Prepared	Hard
Panel A: All students							
STEM	-0.004	-0.030***	-0.004	-0.011	-0.469***	0.039	0.173*
	(0.003)	(0.011)	(0.009)	(0.018)	(0.126)	(0.038)	(0.088)
Intercept	1.00	0.98	1.00	0.99	8.55	0.84	1.88
Std. dev.	0.08	0.20	0.08	0.14	1.09	0.34	0.73
Cutoffs	280	280	190	190	186	190	190
Students	2,978	2,978	1,046	1,046	1,018	1,046	1,046
Student-cutoffs	3,327	3,327	1,159	1,159	1,130	1,159	1,159
Panel B: Students at cutoffs with low cutoff scores							
STEM	-0.008	-0.055***	-0.018	-0.045	-0.783***	-0.006	0.297**
	(0.006)	(0.021)	(0.015)	(0.033)	(0.187)	(0.074)	(0.135)
Intercept	0.99	0.96	1.00	0.98	8.37	0.87	1.74
Std. dev.	0.10	0.26	0.10	0.19	1.12	0.35	0.71
Cutoffs	161	161	104	104	101	104	104
Students	1,637	1,637	525	525	505	525	525
Student-cutoffs	1,703	1,703	547	547	527	547	547
Panel C: Students at cutoffs with high cutoff scores							
STEM	0.000	-0.006	0.000	0.008	-0.313	0.057	0.172
	(0.000)	(0.006)	(0.000)	(0.012)	(0.194)	(0.056)	(0.127)
Intercept	1.00	1.00	1.00	1.01	8.83	0.84	1.89
Std. dev.	0.02	0.07	0.04	0.07	0.94	0.34	0.74
Cutoffs	119	119	86	86	85	86	86
Students	1,445	1,445	545	545	537	545	545
Student-cutoffs	1,624	1,624	612	612	603	612	612

The table presents effects on baccalaureate performance for the survey samples for the surveys where we asked about bacc. outcomes. Outcomes are measured within four years of track assignment and are from the surveys. Prepared is Yes or No for whether the student thinks their school and specialization prepares them well for taking the bacc. Hard is whether they think the bacc. is harder for their curriculum than for others on a three point scale. Not all students reported their exam scores, even among those who reported taking the exam.

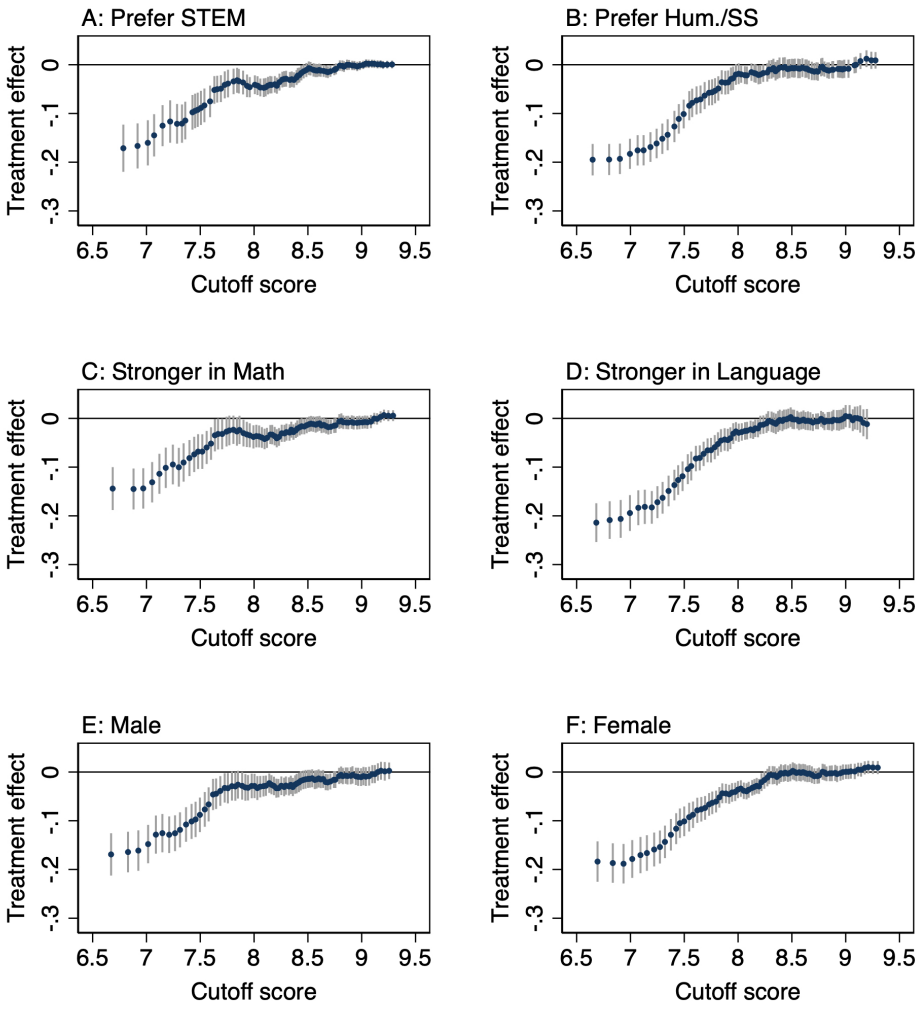
- Effects for the survey samples are roughly similar to those for the 2019 cohort (Table A12).
- Pass rates are higher for the 2019 cohort than for the 2015-2017 cohorts, especially for students at cutoffs with low cutoff scores.
- Effects on self-reported bacc outcomes from the surveys are similar to those on actual bacc. outcomes for the corresponding samples, lending confidence in the quality of the surveys (Table A13).

Table A14: Heterogeneity for effects on baccalaureate performance

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Take the exam									
STEM	-0.011***	-0.010***	-0.012***	-0.001	-0.025***	-0.004	-0.014***	-0.035***	-0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.007)	(0.003)
Intercept	0.95	0.97	0.94	0.96	0.95	0.95	0.96	0.92	0.98
Cutoffs	1,904	973	931	1,664	1,579	1,650	1,684	999	905
Students	62,301	37,376	36,094	38,027	24,062	26,711	35,408	25,474	39,179
Student-cutoffs	73,470	37,376	36,094	45,077	28,060	31,900	41,295	27,204	46,266
Panel B: Pass the exam									
STEM	-0.036***	-0.030***	-0.042***	-0.016***	-0.071***	-0.033***	-0.036***	-0.111***	-0.008**
	(0.004)	(0.004)	(0.007)	(0.004)	(0.007)	(0.006)	(0.005)	(0.010)	(0.003)
Intercept	0.92	0.95	0.89	0.93	0.90	0.91	0.93	0.86	0.97
Cutoffs	1,904	973	931	1,664	1,579	1,650	1,684	999	905
Students	62,301	37,376	36,094	38,027	24,062	26,711	35,408	25,474	39,179
Student-cutoffs	73,470	37,376	36,094	45,077	28,060	31,900	41,295	27,204	46,266
Panel C: Exam score									
STEM	-0.351***	-0.312***	-0.391***	-0.312***	-0.434***	-0.359***	-0.340***	-0.502***	-0.302***
	(0.015)	(0.018)	(0.020)	(0.018)	(0.023)	(0.021)	(0.019)	(0.032)	(0.016)
Intercept	8.08	8.28	7.88	8.17	7.92	7.90	8.24	7.45	8.44
Cutoffs	1,855	945	910	1,621	1,533	1,618	1,648	955	900
Students	59,127	36,282	33,656	36,616	22,306	25,337	33,622	23,153	38,257
Student-cutoffs	69,938	36,282	33,656	43,454	26,154	30,364	39,321	24,751	45,187
Panel D: Pass in STEM									
STEM	0.642***	0.644***	0.640***	0.646***	0.633***	0.573***	0.705***	0.548***	0.674***
	(0.008)	(0.010)	(0.011)	(0.009)	(0.013)	(0.011)	(0.010)	(0.017)	(0.009)
Intercept	0.14	0.20	0.07	0.19	0.05	0.19	0.09	0.02	0.20
Cutoffs	1,411	718	693	1,240	1,165	1,228	1,242	719	692
Students	46,789	28,526	26,695	30,091	16,543	20,141	26,521	17,374	31,116
Student-cutoffs	55,221	28,526	26,695	35,757	19,223	24,127	30,896	18,501	36,720

The table shows heterogeneity for some of the results in Table 4.

Figure A5: Heterogeneity for effects on passing the bacc. by cutoff score and student attributes



The figure shows heterogeneity for the effects in Figure 2 by the specified student attributes.

A5 Additional results for effects on college outcomes

Table A15: Effects on college outcomes: students from the follow-up or peer surveys

	Any	**STEM**				**Hum., law, & social science**				**Other/ unsure**
		Any	Math & CS	Medicine	Economics & Bus.	Any	Humanities	Law	Social science	
Panel A: College plans at the end of high school										
STEM	0.018	0.250***	0.159***	0.035	0.056**	-0.232***	-0.073***	-0.056**	-0.103***	0.000
	(0.020)	(0.036)	(0.026)	(0.025)	(0.026)	(0.034)	(0.021)	(0.023)	(0.022)	(0.024)
Intercept	0.88	0.31	0.08	0.10	0.13	0.41	0.13	0.12	0.15	0.16
Panel B: Initial college enrollment										
STEM	-0.035	0.249***	0.198***	0.015	0.036	-0.266***	-0.126***	-0.093***	-0.047***	-0.018
	(0.025)	(0.037)	(0.030)	(0.022)	(0.026)	(0.031)	(0.021)	(0.022)	(0.017)	(0.027)
Intercept	0.84	0.30	0.11	0.08	0.11	0.38	0.17	0.13	0.08	0.16
Panel C: College enrollment one year after high school										
STEM	-0.037	0.246***	0.192***	0.015	0.039	-0.261***	-0.123***	-0.092***	-0.046***	-0.022
	(0.025)	(0.036)	(0.031)	(0.022)	(0.026)	(0.031)	(0.021)	(0.021)	(0.017)	(0.027)
Intercept	0.82	0.28	0.11	0.08	0.10	0.38	0.17	0.13	0.08	0.16
Panel D: Change in enrollment versus plans in the year after high school										
STEM	-0.055**	-0.004	0.033	-0.020	-0.017	-0.029	-0.050*	-0.036	0.056**	-0.022
	(0.028)	(0.043)	(0.027)	(0.025)	(0.030)	(0.036)	(0.027)	(0.023)	(0.026)	(0.034)
Intercept	-0.06	-0.03	0.02	-0.02	-0.03	-0.03	0.04	0.01	-0.07	-0.00
Cutoffs	280	280	280	280	280	280	280	280	280	280
Students	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978	2,978
Student-cutoffs	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327	3,327

The table is similar to Table 5, but restricted to students from the follow-up or peer surveys. Variables in Panel D are the difference between those in Panels C and A.

Table A16: Effects on college outcomes: students from the follow-up survey

	Any	STEM				Hum., law, & social science				Other/ unsure
		Any	Math & CS	Medicine	Economics & Bus.	Any	Humanities	Law	Social science	
Panel A: College plans at the end of high school										
STEM	0.018	0.178***	0.184***	0.000	-0.006	-0.224***	-0.061	-0.053	-0.110***	0.065
	(0.029)	(0.061)	(0.048)	(0.037)	(0.041)	(0.056)	(0.038)	(0.035)	(0.037)	(0.045)
Intercept	0.88	0.39	0.10	0.13	0.16	0.40	0.13	0.12	0.16	0.10
Panel B: Initial college enrollment										
STEM	-0.027	0.233***	0.217***	-0.005	0.021	-0.241***	-0.089**	-0.110***	-0.042	-0.019
	(0.043)	(0.061)	(0.059)	(0.039)	(0.051)	(0.053)	(0.040)	(0.033)	(0.033)	(0.037)
Intercept	0.84	0.36	0.11	0.09	0.16	0.36	0.13	0.14	0.09	0.12
Panel C: College enrollment one year after high school										
STEM	-0.021	0.223***	0.213***	-0.005	0.015	-0.225***	-0.081**	-0.103***	-0.041	-0.019
	(0.045)	(0.057)	(0.059)	(0.039)	(0.048)	(0.052)	(0.040)	(0.033)	(0.033)	(0.038)
Intercept	0.82	0.36	0.11	0.09	0.16	0.35	0.12	0.13	0.09	0.12
Panel D: Change in enrollment versus plans in the year after high school										
STEM	-0.039	0.045	0.029	-0.005	0.021	-0.001	-0.020	-0.050	0.069*	-0.083
	(0.053)	(0.063)	(0.047)	(0.041)	(0.053)	(0.059)	(0.043)	(0.034)	(0.041)	(0.051)
Intercept	-0.06	-0.03	0.01	-0.04	-0.00	-0.06	-0.00	0.01	-0.07	0.03
Cutoffs	190	190	190	190	190	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159

The table is similar to Table 5, but restricted to students from the follow-up survey. Variables in Panel D are the difference between those in Panels C and A.

Table A17: Effects on college outcomes: students from the second follow-up survey

	Any	STEM				Hum., law, & social science				Other/ unsure
		Any	Math & CS	Medicine	Economics & Bus.	Any	Humanities	Law	Social science	
Panel A: College plans at the end of high school										
STEM	0.040	0.207***	0.196***	0.034	-0.023	-0.173***	-0.016	-0.050	-0.107***	0.006
	(0.031)	(0.058)	(0.043)	(0.039)	(0.045)	(0.059)	(0.037)	(0.040)	(0.039)	(0.038)
Intercept	0.85	0.35	0.09	0.11	0.16	0.37	0.09	0.12	0.16	0.13
Panel B: College enrollment 1.5 years after high school										
STEM	0.001	0.242***	0.204***	0.001	0.038	-0.170***	0.040	-0.123***	-0.087***	-0.071*
	(0.031)	(0.053)	(0.054)	(0.037)	(0.043)	(0.051)	(0.036)	(0.039)	(0.029)	(0.039)
Intercept	0.87	0.35	0.13	0.10	0.12	0.32	0.04	0.16	0.12	0.19
Panel C: Change in enrollment versus plans in the 1.5 years after high school										
STEM	-0.038	0.036	0.007	-0.033	0.061	0.004	0.057	-0.073*	0.020	-0.078
	(0.038)	(0.063)	(0.049)	(0.037)	(0.052)	(0.059)	(0.041)	(0.043)	(0.040)	(0.055)
Intercept	0.01	0.00	0.05	-0.01	-0.04	-0.05	-0.05	0.04	-0.04	0.06
Cutoffs	198	198	198	198	198	198	198	198	198	198
Students	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199

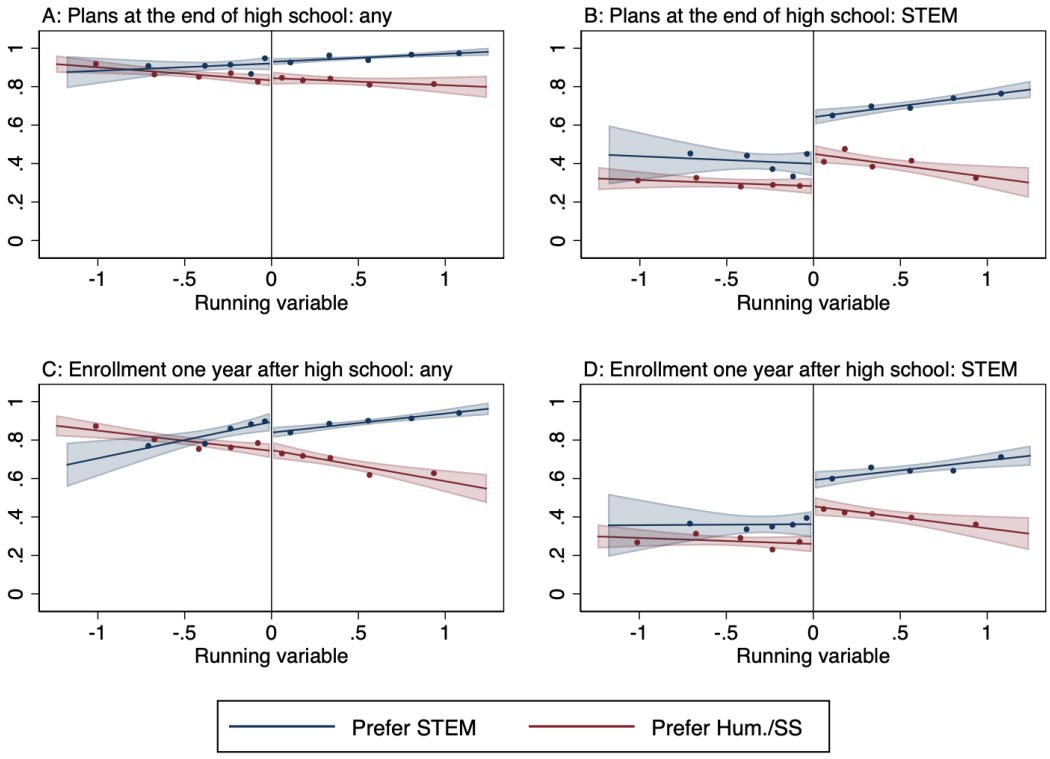
The table is similar to Table 5, but restricted to students from the second follow-up survey, which occurred one and a half years after high school graduation. Variables in Panel C are the difference between those in Panels B and A. There is no panel for initial college enrollment because this wasn't asked in the second follow-up survey.

Table A18: Robustness for effects on college outcomes

	Main	**Alternative bandwidths**				**Adding covariates**
		0.75	1.00	1.50	1.75	
Panel A: College plans at the end of high school: any college						
STEM	0.010	0.007	0.021	0.019	0.022	0.015
	(0.018)	(0.021)	(0.019)	(0.017)	(0.017)	(0.018)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987
Panel B: College plans at the end of high school: STEM						
STEM	0.233***	0.242***	0.242***	0.229***	0.230***	0.230***
	(0.035)	(0.039)	(0.036)	(0.034)	(0.032)	(0.035)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987
Panel C: College enrollment one year after high school: any college						
STEM	-0.037	-0.058**	-0.047*	-0.031	-0.024	-0.034
	(0.025)	(0.027)	(0.025)	(0.025)	(0.025)	(0.025)
Cutoffs	280	257	273	286	289	280
Students	2,978	2,223	2,664	3,189	3,323	2,978
Student-cutoffs	3,327	2,520	2,991	3,555	3,692	3,327
Panel D: College enrollment one year after high school: STEM						
STEM	0.246***	0.243***	0.235***	0.251***	0.248***	0.243***
	(0.036)	(0.040)	(0.035)	(0.033)	(0.032)	(0.035)
Cutoffs	280	257	273	286	289	280
Students	2,978	2,223	2,664	3,189	3,323	2,978
Student-cutoffs	3,327	2,520	2,991	3,555	3,692	3,327

The table shows robustness for some of the results in Table 5. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling.

Figure A6: Graphical depiction of effects on college outcomes



The figure plots RD treatment effects for the outcomes in Table A18.

Table A19: Heterogeneity for effects on college outcomes

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: College plans at the end of high school: any college									
STEM	0.010	0.009	0.010	-0.003	-0.007	0.110***	-0.030	-0.043	0.044*
	(0.018)	(0.023)	(0.026)	(0.029)	(0.025)	(0.042)	(0.020)	(0.030)	(0.026)
Intercept	0.87	0.92	0.83	0.88	0.88	0.76	0.93	0.86	0.92
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894
Panel B: College plans at the end of high school: STEM									
STEM	0.233***	0.270***	0.196***	0.267***	0.199***	0.293***	0.207***	0.208***	0.226***
	(0.035)	(0.048)	(0.045)	(0.050)	(0.052)	(0.058)	(0.041)	(0.062)	(0.046)
Intercept	0.31	0.36	0.27	0.36	0.29	0.31	0.31	0.25	0.41
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894
Panel C: College enrollment one year after high school: any college									
STEM	-0.037	-0.065**	-0.009	-0.055	-0.058	0.019	-0.054*	-0.089*	-0.002
	(0.025)	(0.032)	(0.035)	(0.041)	(0.038)	(0.050)	(0.032)	(0.046)	(0.029)
Intercept	0.82	0.90	0.74	0.85	0.79	0.76	0.84	0.77	0.91
Cutoffs	280	143	137	214	209	194	234	161	119
Students	2,978	1,600	1,727	1,426	1,497	1,028	1,891	1,637	1,445
Student-cutoffs	3,327	1,600	1,727	1,591	1,658	1,146	2,098	1,703	1,624
Panel D: College enrollment one year after high school: STEM									
STEM	0.246***	0.259***	0.233***	0.221***	0.287***	0.276***	0.210***	0.219***	0.297***
	(0.036)	(0.052)	(0.040)	(0.065)	(0.046)	(0.060)	(0.044)	(0.052)	(0.050)
Intercept	0.28	0.32	0.25	0.39	0.21	0.30	0.28	0.22	0.34
Cutoffs	280	143	137	214	209	194	234	161	119
Students	2,978	1,600	1,727	1,426	1,497	1,028	1,891	1,637	1,445
Student-cutoffs	3,327	1,600	1,727	1,591	1,658	1,146	2,098	1,703	1,624

The table shows heterogeneity for some of the results in Table 5.

Table A20: Effects on other college outcomes

	Type of college				**Paying for college**			**Pass winter exams**	**Expect to finish**
	Any	Public	Private	Outside Romania	Scholar-ship	Tuition exemption	Out of pocket		
Panel A: All students									
STEM	-0.021	-0.018	-0.019	0.015	-0.125***	0.084	0.002	-0.020	-0.025
	(0.045)	(0.048)	(0.016)	(0.013)	(0.046)	(0.060)	(0.052)	(0.132)	(0.134)
Intercept	0.82	0.78	0.04	0.00	0.27	0.35	0.27	3.24	3.28
Std. dev.	0.38	0.42	0.13	0.17	0.43	0.49	0.45	1.11	1.19
Cutoffs	190	190	190	190	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159
Panel B: Students at cutoffs with low cutoff scores									
STEM	-0.124	-0.133	0.009	-0.001	-0.235***	0.013	-0.026	-0.385	-0.288
	(0.087)	(0.083)	(0.019)	(0.006)	(0.076)	(0.091)	(0.107)	(0.241)	(0.252)
Intercept	0.82	0.79	0.01	0.02	0.32	0.31	0.29	3.34	3.21
Std. dev.	0.44	0.45	0.14	0.09	0.39	0.46	0.45	1.25	1.32
Cutoffs	104	104	104	104	104	104	104	104	104
Students	525	525	525	525	525	525	525	525	525
Student-cutoffs	547	547	547	547	547	547	547	547	547
Panel C: Students at cutoffs with high cutoff scores									
STEM	-0.004	0.007	-0.022	0.011	-0.105	0.205**	-0.049	0.151	-0.068
	(0.046)	(0.058)	(0.025)	(0.025)	(0.073)	(0.090)	(0.070)	(0.152)	(0.139)
Intercept	0.91	0.86	0.04	0.01	0.27	0.36	0.31	3.33	3.62
Std. dev.	0.31	0.38	0.13	0.22	0.46	0.50	0.44	0.93	1.02
Cutoffs	86	86	86	86	86	86	86	86	86
Students	545	545	545	545	545	545	545	545	545
Student-cutoffs	612	612	612	612	612	612	612	612	612

The table shows effects on other college outcomes. 1.25 point bandwidth. Variables are from the follow-up survey. "Type of college" and "Paying for college" are for college enrollment one year after high school. "Pass winter exams" and "Expect to finish" are on a scale of 1 to 4. "Pass winter exams" was not asked to students who were never enrolled in college. It is set to 1 for these students. "Expect to finish" was not asked to students who were not enrolled in college one year after high school. It is set to 1 for these students.

A6 Additional results for effects on academic belief and preference outcomes

Table A21: Effects on beliefs about own abilities for high school subjects: students from the follow-up survey

	STEM subjects	**Humanities subjects**	**Social science subjects**
Panel A: Beliefs at the end of high school			
STEM	0.966***	-0.038	-0.409***
	(0.139)	(0.116)	(0.140)
Intercept	2.65	4.00	3.84
Std. dev.	1.28	0.84	1.16
Panel B: Beliefs one year after high school			
STEM	0.744***	-0.267***	-0.745***
	(0.124)	(0.087)	(0.139)
Intercept	2.96	4.20	4.06
Std. dev.	1.10	0.84	1.13
Panel C: Change in beliefs in the year after high school			
STEM	-0.222	-0.229**	-0.336**
	(0.140)	(0.105)	(0.141)
Intercept	0.31	0.20	0.22
Std. dev.	1.10	0.94	1.13
Cutoffs	190	190	190
Students	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159

The table is similar to Panels A and B of Table 6, but restricted to students from the follow-up survey. The variables in Panel C are the difference between those in Panels B and A.

Table A22: Effects on beliefs about own abilities and preferences for college subjects with no imputations for missing responses

	STEM subjects	**Subjects that involve reading and writing**	**Subjects that involve memorization**
Panel A: Beliefs one year after high school			
STEM	0.901***	-0.409***	-0.280*
	(0.152)	(0.124)	(0.156)
Intercept	2.85	3.64	3.59
Std. dev.	1.19	1.05	1.07
Panel B: Preferences one year after high school			
STEM	1.04***	-0.584***	-0.408**
	(0.136)	(0.145)	(0.157)
Intercept	2.75	3.66	3.47
Std. dev.	1.27	1.05	1.12
Cutoffs	171	171	171
Students	865	865	865
Student-cutoffs	965	965	965

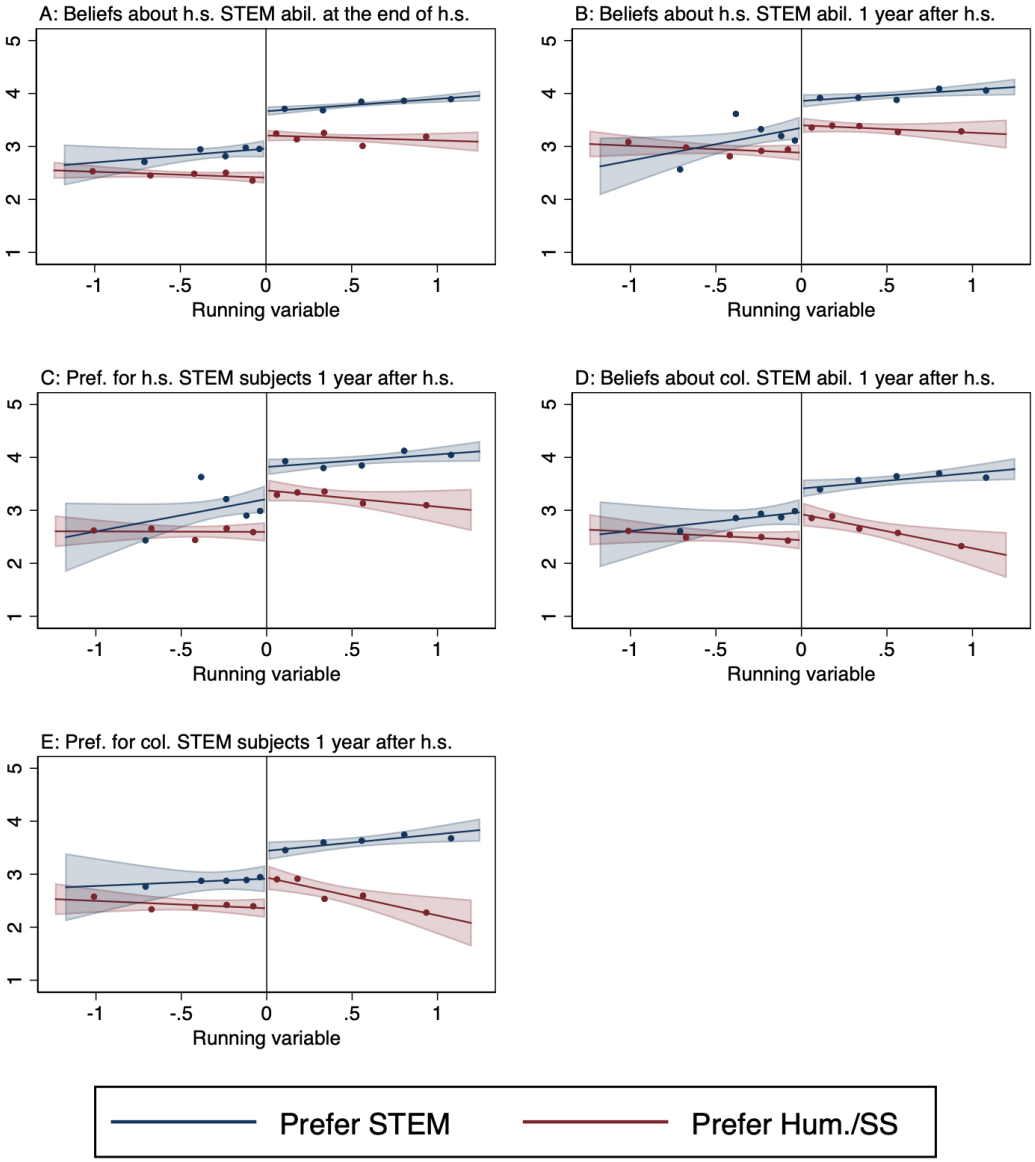
The table is analogous to Table 7, but it does not impute values of 1 for students for whom the college belief and preference questions were not asked (those who never attended college at the time of the follow-up survey).

Table A23: Robustness for effects on academic belief and preference outcomes

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: Beliefs about own high school STEM abilities at the end of high school						
STEM	0.873***	0.832***	0.868***	0.866***	0.878***	0.870***
	(0.077)	(0.091)	(0.079)	(0.073)	(0.071)	(0.075)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987
Panel B: Beliefs about own high school STEM abilities one year after high school						
STEM	0.744***	0.793***	0.701***	0.725***	0.736***	0.745***
	(0.124)	(0.138)	(0.130)	(0.117)	(0.111)	(0.122)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159
Panel C: Preferences for high school STEM subjects one year after high school						
STEM	1.01***	1.13***	0.949***	1.01***	1.01***	1.01***
	(0.151)	(0.169)	(0.164)	(0.144)	(0.139)	(0.150)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159
Panel D: Beliefs about own college STEM abilities one year after high school						
STEM	0.659***	0.580***	0.542***	0.631***	0.640***	0.654***
	(0.151)	(0.183)	(0.157)	(0.144)	(0.136)	(0.148)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159
Panel E: Preferences for college STEM subjects one year after high school						
STEM	0.776***	0.736***	0.679***	0.765***	0.760***	0.769***
	(0.149)	(0.179)	(0.152)	(0.144)	(0.136)	(0.148)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159

The table shows robustness for some of the results in Tables 6 and 7. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling.

Figure A7: Graphical depiction of effects on academic belief and preference outcomes



The figure plots RD treatment effects for the outcomes in Table A23.

Table A24: Heterogeneity for effects on academic belief and preference outcomes

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Beliefs about own high school STEM abilities at the end of high school									
STEM	0.873***	0.789***	0.956***	0.853***	0.916***	0.765***	0.912***	0.876***	0.854***
	(0.077)	(0.106)	(0.092)	(0.123)	(0.105)	(0.127)	(0.093)	(0.125)	(0.110)
Intercept	2.60	2.85	2.36	2.85	2.41	2.75	2.51	2.38	2.87
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894
Panel B: Beliefs about own high school STEM abilities one year after high school									
STEM	0.744***	0.718***	0.770***	0.797***	0.737***	0.823***	0.656***	0.668**	0.693***
	(0.124)	(0.160)	(0.159)	(0.212)	(0.171)	(0.213)	(0.161)	(0.259)	(0.168)
Intercept	2.96	3.16	2.76	3.17	2.72	3.01	2.97	2.77	3.17
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612
Panel C: Preferences for high school STEM subjects one year after high school									
STEM	1.01***	0.850***	1.17***	1.03***	1.14***	1.14***	0.952***	1.07***	1.04***
	(0.151)	(0.184)	(0.208)	(0.275)	(0.192)	(0.290)	(0.191)	(0.287)	(0.208)
Intercept	2.72	3.00	2.43	3.01	2.39	2.78	2.69	2.41	2.83
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612
Panel D: Beliefs about own college STEM abilities one year after high school									
STEM	0.659***	0.622***	0.696***	0.773***	0.554**	0.725**	0.579***	0.263	0.895***
	(0.151)	(0.197)	(0.203)	(0.211)	(0.223)	(0.315)	(0.208)	(0.269)	(0.194)
Intercept	2.57	2.80	2.34	2.74	2.36	2.53	2.63	2.52	2.69
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612
Panel E: Preferences for college STEM subjects one year after high school									
STEM	0.776***	0.723***	0.829***	0.856***	0.748***	1.050***	0.614***	0.396	0.914***
	(0.149)	(0.194)	(0.196)	(0.220)	(0.226)	(0.330)	(0.203)	(0.268)	(0.182)
Intercept	2.48	2.72	2.25	2.73	2.22	2.25	2.60	2.44	2.66
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612

The table shows heterogeneity for some of the results in Tables 6 and 7.

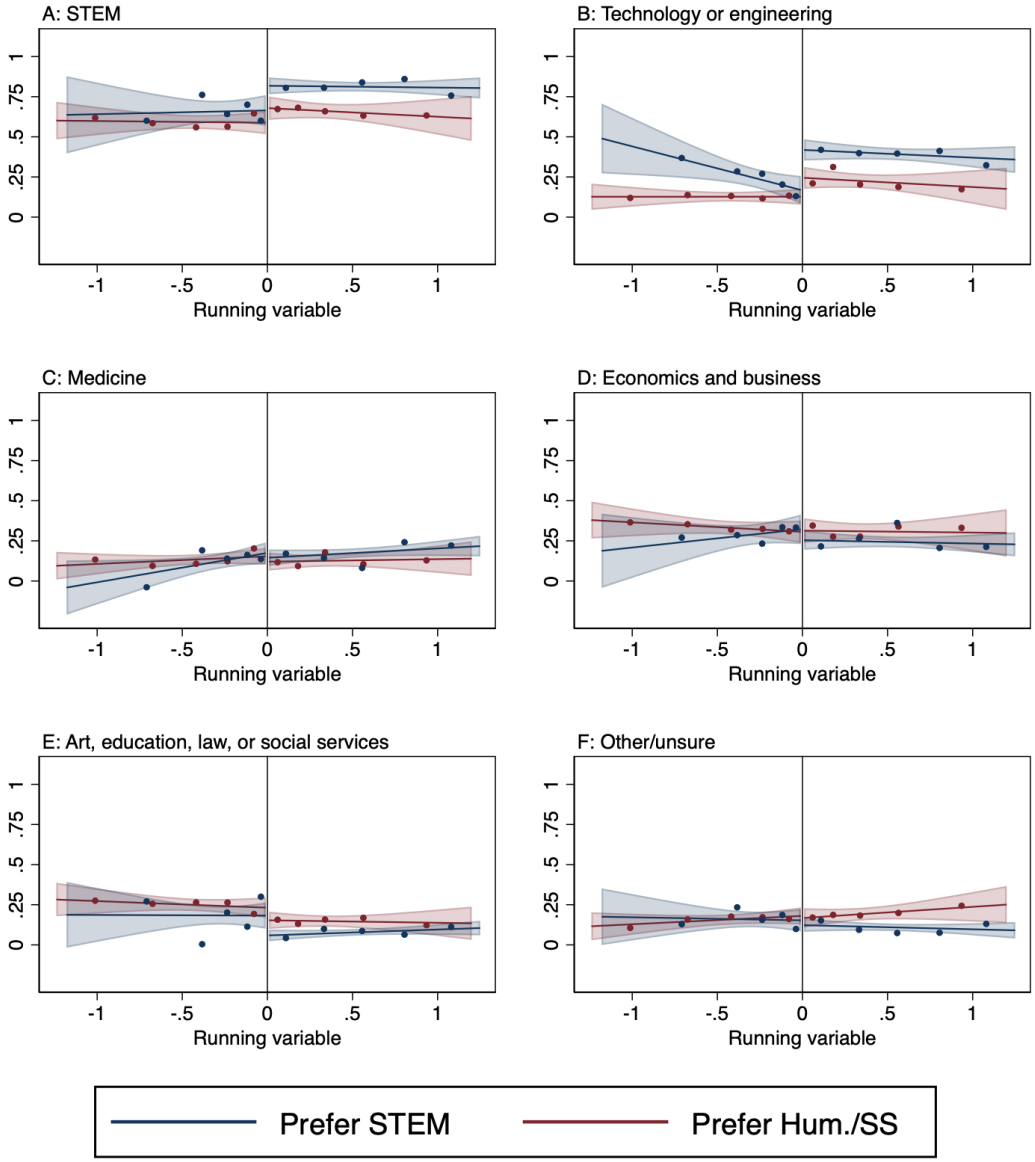
A7 Additional results for effects on career plans

Table A25: Robustness for effects on career plans one year after high school

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: STEM						
STEM	0.173***	0.141**	0.170***	0.162***	0.156***	0.168***
	(0.056)	(0.064)	(0.059)	(0.054)	(0.051)	(0.055)
Panel B: Technology or engineering						
STEM	0.254***	0.245***	0.251***	0.242***	0.225***	0.246***
	(0.051)	(0.059)	(0.052)	(0.049)	(0.046)	(0.048)
Panel C: Medicine						
STEM	-0.041	-0.063	-0.063	-0.039	-0.026	-0.035
	(0.044)	(0.052)	(0.047)	(0.041)	(0.039)	(0.045)
Panel D: Economics and business						
STEM	-0.040	-0.040	-0.018	-0.040	-0.043	-0.043
	(0.063)	(0.071)	(0.066)	(0.062)	(0.059)	(0.063)
Panel E: Art, education, law, or social services						
STEM	-0.145***	-0.155***	-0.150***	-0.141***	-0.141***	-0.141***
	(0.046)	(0.055)	(0.050)	(0.046)	(0.043)	(0.044)
Panel F: Other/unsure						
STEM	-0.028	0.013	-0.020	-0.021	-0.016	-0.027
	(0.040)	(0.042)	(0.040)	(0.038)	(0.036)	(0.040)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159

The table shows robustness for the results in Table 8. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A8: Graphical depiction of effects on career plans one year after high school



The figure plots RD treatment effects for the outcomes in Table A25.

Table A26: Heterogeneity for effects on career plans one year after high school

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: STEM									
STEM	0.173***	0.210**	0.135**	0.224**	0.187**	0.242**	0.136*	0.235**	0.180**
	(0.056)	(0.087)	(0.060)	(0.090)	(0.088)	(0.108)	(0.072)	(0.115)	(0.071)
Intercept	0.60	0.62	0.58	0.68	0.49	0.59	0.61	0.43	0.68
Panel B: Technology or engineering									
STEM	0.254***	0.333***	0.175**	0.245***	0.257***	0.360***	0.183***	0.129	0.339***
	(0.051)	(0.072)	(0.067)	(0.084)	(0.063)	(0.119)	(0.051)	(0.105)	(0.066)
Intercept	0.10	0.10	0.10	0.17	0.07	0.21	0.09	0.19	0.06
Panel C: Medicine									
STEM	-0.041	-0.033	-0.049	-0.051	-0.035	-0.084*	-0.014	-0.050	0.002
	(0.044)	(0.056)	(0.059)	(0.070)	(0.059)	(0.045)	(0.068)	(0.065)	(0.070)
Intercept	0.17	0.17	0.17	0.14	0.16	0.09	0.18	0.11	0.18
Panel D: Economics and business									
STEM	-0.040	-0.090	0.009	0.030	-0.035	-0.034	-0.033	0.157*	-0.161
	(0.063)	(0.072)	(0.093)	(0.094)	(0.088)	(0.117)	(0.077)	(0.080)	(0.102)
Intercept	0.33	0.35	0.31	0.37	0.25	0.29	0.33	0.12	0.44
Panel E: Art, education, law, or social services									
STEM	-0.145***	-0.169**	-0.121**	-0.166**	-0.202***	-0.169**	-0.140**	-0.228**	-0.173***
	(0.046)	(0.072)	(0.049)	(0.067)	(0.070)	(0.077)	(0.062)	(0.112)	(0.056)
Intercept	0.23	0.22	0.24	0.18	0.32	0.18	0.26	0.36	0.22
Panel F: Other/unsure									
STEM	-0.028	-0.041	-0.014	-0.058	0.015	-0.074	0.004	-0.007	-0.008
	(0.040)	(0.056)	(0.050)	(0.065)	(0.051)	(0.101)	(0.047)	(0.090)	(0.044)
Intercept	0.17	0.16	0.18	0.14	0.19	0.23	0.13	0.21	0.10
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612

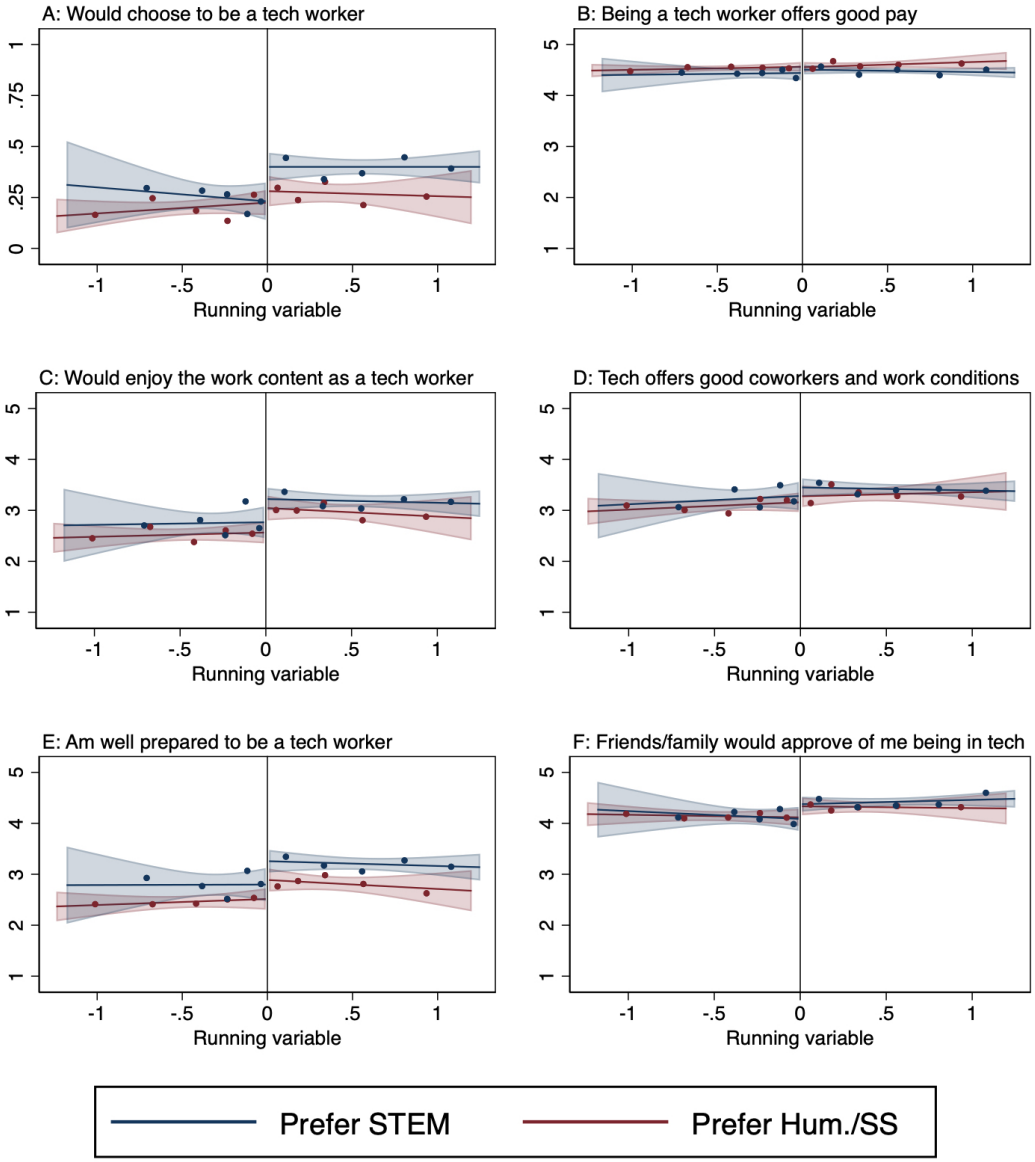
The table shows heterogeneity for the results in Table 8. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A27: Robustness for effects on career choices and beliefs 1.5 years after high school

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: I would choose to be a tech worker						
STEM	0.146***	0.193***	0.149***	0.139***	0.114**	0.139***
	(0.047)	(0.056)	(0.051)	(0.046)	(0.046)	(0.046)
Panel B: Being a tech worker offers good pay						
STEM	0.037	0.124	0.108	0.052	0.044	0.046
	(0.077)	(0.094)	(0.082)	(0.077)	(0.072)	(0.075)
Panel C: I would enjoy the work content as a tech worker						
STEM	0.614***	0.845***	0.693***	0.538***	0.489***	0.566***
	(0.185)	(0.211)	(0.194)	(0.177)	(0.170)	(0.176)
Panel D: Tech offers good coworkers and work conditions						
STEM	0.185	0.238	0.171	0.152	0.142	0.160
	(0.157)	(0.183)	(0.163)	(0.148)	(0.144)	(0.151)
Panel E: I am well prepared to be a tech worker						
STEM	0.543***	0.685***	0.523**	0.480**	0.493***	0.500***
	(0.199)	(0.215)	(0.203)	(0.190)	(0.182)	(0.183)
Panel F: My friends/family would approve of me being a tech worker						
STEM	0.336**	0.462***	0.351**	0.291**	0.286**	0.334**
	(0.135)	(0.148)	(0.145)	(0.132)	(0.127)	(0.139)
Cutoffs	198	165	187	201	207	198
Students	1,089	788	963	1,158	1,205	1,089
Student-cutoffs	1,199	883	1,068	1,271	1,318	1,199

The table shows robustness for the results in Panel A of Table 9. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A9: Graphical depiction of effects on career choices and beliefs 1.5 years after high school



The figure plots RD treatment effects for the outcomes in Table A27.

Table A28: Heterogeneity for effects on career choices and beliefs 1.5 years after high school

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: I would choose to be a tech worker									
STEM	0.146***	0.222***	0.071	0.081	0.238***	0.212**	0.085	0.235***	0.130*
	(0.047)	(0.066)	(0.056)	(0.089)	(0.066)	(0.096)	(0.061)	(0.082)	(0.066)
Intercept	0.20	0.18	0.23	0.29	0.12	0.23	0.22	0.12	0.21
Panel B: Being a tech worker offers good pay									
STEM	0.037	0.085	-0.012	-0.025	0.213**	-0.183	0.097	0.213	-0.023
	(0.077)	(0.101)	(0.095)	(0.148)	(0.098)	(0.150)	(0.084)	(0.153)	(0.118)
Intercept	4.50	4.44	4.56	4.44	4.51	4.62	4.48	4.38	4.44
Panel C: I would enjoy the work content as a tech worker									
STEM	0.614***	0.604**	0.624***	0.676**	0.815***	0.725**	0.304	0.861**	0.576**
	(0.185)	(0.281)	(0.216)	(0.273)	(0.232)	(0.331)	(0.214)	(0.355)	(0.252)
Intercept	2.58	2.65	2.52	2.87	2.48	2.97	2.59	2.53	2.57
Panel D: Tech offers good coworkers and work conditions									
STEM	0.185	0.225	0.146	-0.068	0.462**	0.268	-0.019	0.702**	0.057
	(0.157)	(0.225)	(0.193)	(0.245)	(0.200)	(0.291)	(0.199)	(0.295)	(0.240)
Intercept	3.20	3.23	3.16	3.52	2.96	3.45	3.24	2.82	3.30
Panel E: I am well prepared to be a tech worker									
STEM	0.543***	0.605**	0.481**	0.703**	0.777***	0.669**	0.326	0.639**	0.691**
	(0.199)	(0.298)	(0.236)	(0.312)	(0.255)	(0.335)	(0.225)	(0.321)	(0.270)
Intercept	2.60	2.71	2.49	2.82	2.34	2.92	2.49	2.51	2.60
Panel F: My friends/family would approve of me being a tech worker									
STEM	0.336**	0.384**	0.287*	0.781***	0.154	0.812***	-0.010	-0.001	0.688***
	(0.135)	(0.186)	(0.166)	(0.265)	(0.156)	(0.284)	(0.165)	(0.210)	(0.195)
Intercept	4.05	4.01	4.09	3.87	4.26	3.98	4.17	4.30	3.85
Cutoffs	198	94	104	118	117	101	143	107	91
Students	1,089	575	624	494	501	350	665	606	515
Student-cutoffs	1,199	575	624	540	550	373	728	618	581

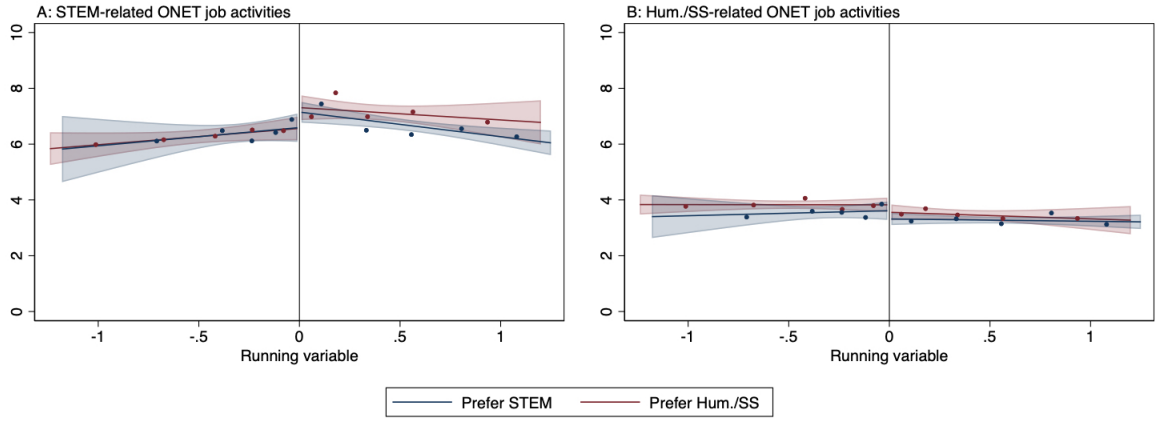
The table shows heterogeneity for the results in Panel A of Table 9. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A29: Robustness for effects on preferences over O*NET job activities 1.5 years after high school

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: STEM-related ONET job activities						
STEM	0.828***	1.09***	0.916***	0.729***	0.732***	0.729***
	(0.288)	(0.318)	(0.304)	(0.269)	(0.264)	(0.268)
Panel B: Hum./SS-related ONET job activities						
STEM	-0.371*	-0.248	-0.339	-0.383*	-0.360*	-0.330
	(0.220)	(0.266)	(0.251)	(0.211)	(0.205)	(0.211)
Cutoffs	198	165	187	201	207	198
Students	1,089	788	963	1,158	1,205	1,089
Student-cutoffs	1,199	883	1,068	1,271	1,318	1,199

The table shows robustness for some of the results Table 10. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A10: Graphical depiction of effects on preferences over O*NET job activities 1.5 years after high school



The figure plots RD treatment effects for the outcomes in Table A29.

Table A30: Heterogeneity for effects on preferences over O*NET job activities 1.5 years after high school

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: STEM-related ONET job activities									
STEM	0.828***	0.714*	0.942**	1.68***	0.475	0.990*	0.621*	0.736	0.787*
	(0.288)	(0.405)	(0.371)	(0.488)	(0.424)	(0.529)	(0.347)	(0.445)	(0.412)
Intercept	6.60	6.63	6.58	6.44	6.74	7.42	6.26	6.79	6.64
Panel B: Hum./SS-related ONET job activities									
STEM	-0.371*	-0.390	-0.353	0.029	-0.774***	-0.140	-0.337	-0.768**	-0.437
	(0.220)	(0.270)	(0.323)	(0.366)	(0.289)	(0.330)	(0.262)	(0.361)	(0.275)
Intercept	3.80	3.71	3.89	3.37	4.08	3.19	4.11	4.24	3.81
Cutoffs	198	94	104	118	117	101	143	107	91
Students	1,089	575	624	494	501	350	665	606	515
Student-cutoffs	1,199	575	624	540	550	373	728	618	581

The table shows heterogeneity for some of the results Table 10. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

A8 Additional results for effects on high school and college satisfaction, curricular fit, and regret

Table A31: Effects on high school satisfaction and curricular fit: students from the follow-up survey

	Liked the:				**Curriculum was good fit**
	Experience	Curriculum	Peers	Teachers	
Panel A: End of high school					
STEM	0.127	0.185	0.242**	0.228*	0.275***
	(0.125)	(0.117)	(0.117)	(0.131)	(0.100)
Intercept	3.63	3.17	3.47	3.39	3.22
Std. dev.	0.99	1.00	1.09	1.02	0.85
Panel B: One year after high school					
STEM	0.217*	-0.004	0.287**	0.128	-0.123
	(0.110)	(0.137)	(0.138)	(0.130)	(0.118)
Intercept	3.90	3.13	3.82	3.75	3.49
Std. dev.	0.89	1.06	1.08	0.93	1.02
Panel C: Change in the year after high school					
STEM	0.090	-0.189	0.045	-0.100	-0.398***
	(0.118)	(0.138)	(0.140)	(0.134)	(0.124)
Intercept	0.27	-0.04	0.34	0.36	0.27
Std. dev.	1.06	1.25	1.15	1.10	1.21
Cutoffs	190	190	190	190	190
Students	1,046	1,046	1,046	1,046	1,046
Student-cutoffs	1,159	1,159	1,159	1,159	1,159

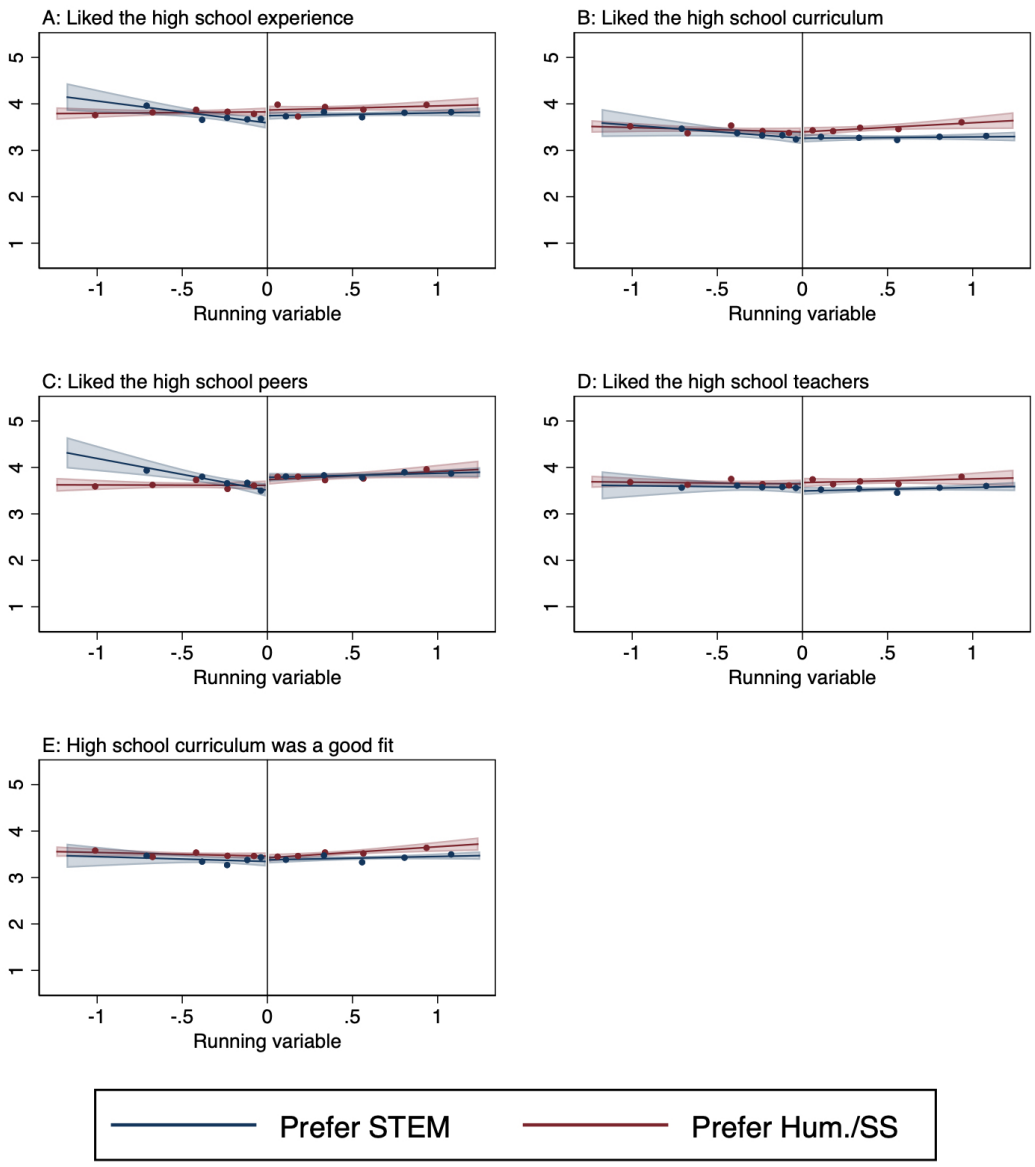
The table is similar to Panels A and B of Table 11, but restricted to students from the follow-up survey. The variables in Panel C are the difference between those in Panels B and A.

Table A32: Robustness for effects on high school satisfaction and curricular fit at the end of high school

	Main	**Alternative bandwidths**				**Adding covariates**
		0.75	1.00	1.50	1.75	
Panel A: Liked the high school experience						
STEM	0.113*	0.133*	0.113	0.109*	0.114*	0.122*
	(0.068)	(0.077)	(0.070)	(0.066)	(0.062)	(0.067)
Panel B: Liked the high school curriculum						
STEM	0.002	0.049	0.027	-0.019	-0.017	0.019
	(0.066)	(0.076)	(0.068)	(0.063)	(0.061)	(0.065)
Panel C: Liked the high school peers						
STEM	0.233***	0.246***	0.262***	0.222***	0.228***	0.214***
	(0.072)	(0.078)	(0.072)	(0.072)	(0.069)	(0.071)
Panel D: Liked the high school teachers						
STEM	-0.022	0.040	-0.000	-0.011	-0.023	-0.015
	(0.068)	(0.084)	(0.072)	(0.066)	(0.065)	(0.068)
Panel E: High school curriculum was a good fit for own abilities						
STEM	0.001	-0.019	0.005	-0.006	0.016	0.012
	(0.053)	(0.065)	(0.058)	(0.051)	(0.049)	(0.052)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987

The table shows robustness for the results in Panel A of Table 11. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A11: Graphical depiction of effects on high school satisfaction and curricular fit at the end of high school



The figure plots RD treatment effects for the outcomes in Table A32.

Table A33: Heterogeneity for effects on high school satisfaction and curricular fit at the end of high school

	All	**Prefer**		**Stronger in**		**Gender**		**Cutoff score**	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Liked the high school experience									
STEM	0.113*	0.171*	0.054	0.112	0.164*	0.096	0.112	0.260**	0.013
	(0.068)	(0.094)	(0.084)	(0.113)	(0.084)	(0.127)	(0.083)	(0.111)	(0.098)
Intercept	3.69	3.56	3.82	3.62	3.73	3.61	3.75	3.60	3.74
Panel B: Liked the high school curriculum									
STEM	0.002	-0.002	0.007	-0.001	-0.010	0.037	-0.006	0.107	-0.150
	(0.066)	(0.087)	(0.083)	(0.110)	(0.091)	(0.133)	(0.071)	(0.107)	(0.108)
Intercept	3.32	3.26	3.38	3.25	3.42	3.13	3.41	3.37	3.32
Panel C: Liked the high school peers									
STEM	0.233***	0.309***	0.156*	0.139	0.356***	0.160	0.235***	0.352***	0.169
	(0.072)	(0.091)	(0.094)	(0.118)	(0.106)	(0.121)	(0.090)	(0.133)	(0.109)
Intercept	3.53	3.47	3.60	3.59	3.42	3.75	3.43	3.44	3.58
Panel D: Liked the high school teachers									
STEM	-0.022	-0.082	0.037	-0.109	0.059	0.026	-0.025	0.094	-0.175*
	(0.068)	(0.086)	(0.088)	(0.111)	(0.086)	(0.139)	(0.074)	(0.114)	(0.096)
Intercept	3.60	3.56	3.64	3.52	3.64	3.48	3.65	3.60	3.63
Panel E: High school curriculum was a good fit for own abilities									
STEM	0.001	0.037	-0.035	-0.060	0.074	-0.019	-0.017	0.202***	-0.089
	(0.053)	(0.069)	(0.064)	(0.087)	(0.076)	(0.108)	(0.062)	(0.069)	(0.088)
Intercept	3.39	3.33	3.45	3.40	3.36	3.32	3.45	3.28	3.42
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894

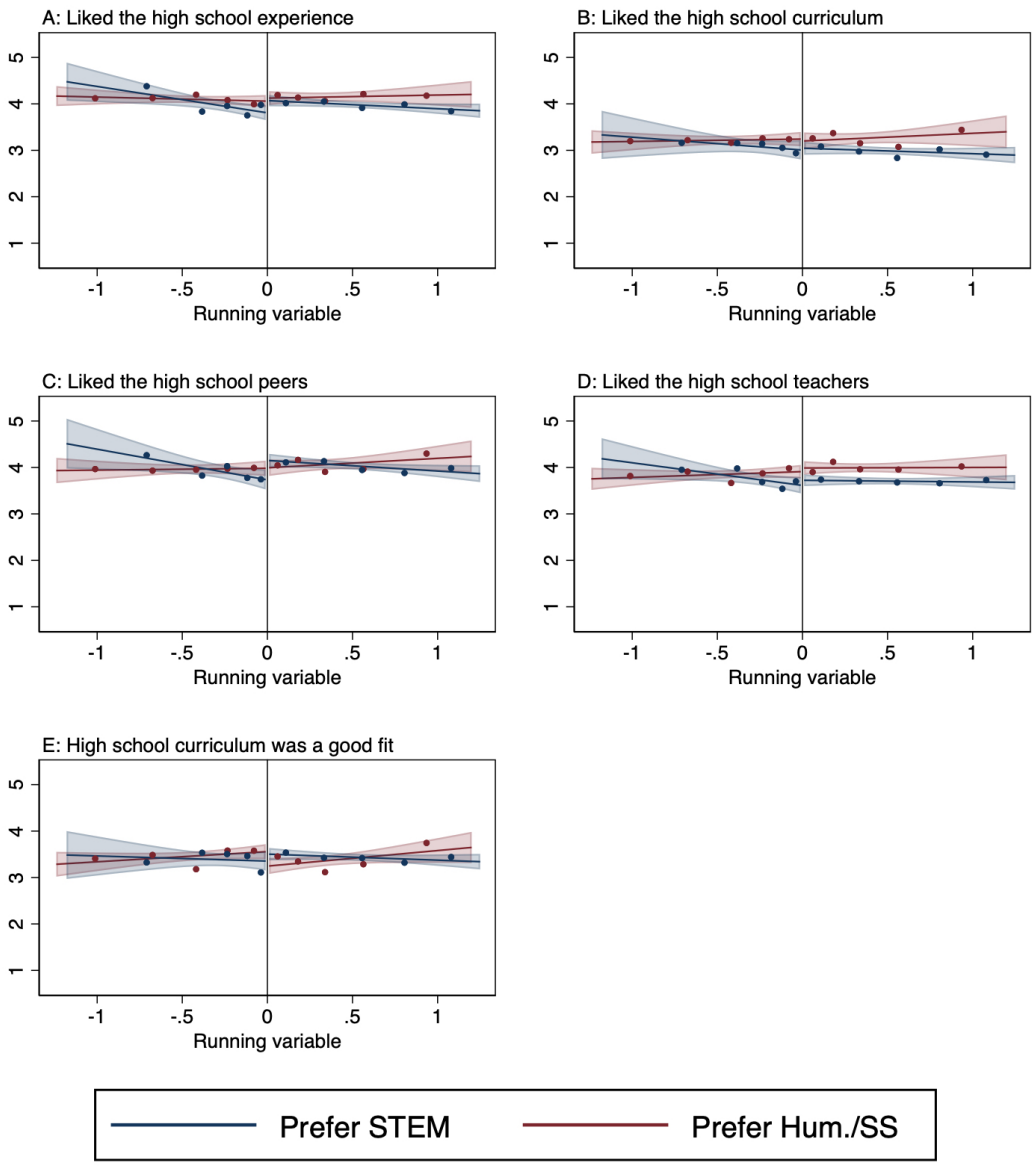
The table shows heterogeneity for the results in Panel A of Table 11. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A34: Robustness for effects on high school satisfaction and curricular fit one year after high school

	Main	**Alternative bandwidths**				**Adding covariates**
		0.75	1.00	1.50	1.75	
Panel A: Liked the high school experience						
STEM	0.217*	0.278**	0.197	0.175*	0.141	0.206*
	(0.110)	(0.132)	(0.120)	(0.106)	(0.105)	(0.108)
Panel B: Liked the high school curriculum						
STEM	-0.004	0.037	-0.053	-0.022	-0.039	0.003
	(0.137)	(0.157)	(0.147)	(0.134)	(0.129)	(0.138)
Panel C: Liked the high school peers						
STEM	0.287**	0.366**	0.283*	0.232*	0.211*	0.284**
	(0.138)	(0.168)	(0.150)	(0.133)	(0.127)	(0.137)
Panel D: Liked the high school teachers						
STEM	0.128	0.158	0.128	0.067	0.077	0.136
	(0.130)	(0.143)	(0.137)	(0.126)	(0.119)	(0.132)
Panel E: High school curriculum was a good fit for own abilities						
STEM	-0.123	-0.055	-0.058	-0.143	-0.126	-0.114
	(0.118)	(0.135)	(0.129)	(0.114)	(0.112)	(0.116)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159

The table shows robustness for the results in Panel B of Table 11. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A12: Graphical depiction of effects on high school satisfaction and curricular fit one year after high school



The figure plots RD treatment effects for the outcomes in Table A34.

Table A35: Heterogeneity for effects on high school satisfaction and curricular fit one year after high school

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Liked the high school experience									
STEM	0.217*	0.335**	0.099	0.376**	0.161	0.709***	-0.088	0.120	0.381***
	(0.110)	(0.136)	(0.156)	(0.172)	(0.136)	(0.246)	(0.134)	(0.225)	(0.126)
Intercept	3.90	3.77	4.03	3.85	3.90	3.54	4.02	3.98	3.72
Panel B: Liked the high school curriculum									
STEM	-0.004	0.043	-0.050	0.140	0.010	0.187	-0.212	0.015	0.037
	(0.137)	(0.159)	(0.208)	(0.219)	(0.179)	(0.309)	(0.161)	(0.277)	(0.168)
Intercept	3.13	3.02	3.25	3.03	3.13	2.91	3.28	3.19	3.03
Panel C: Liked the high school peers									
STEM	0.287**	0.543***	0.031	0.462**	0.220	0.567**	0.064	0.091	0.422*
	(0.138)	(0.171)	(0.194)	(0.210)	(0.218)	(0.260)	(0.184)	(0.235)	(0.217)
Intercept	3.82	3.66	3.97	3.76	3.80	3.79	3.87	3.99	3.68
Panel D: Liked the high school teachers									
STEM	0.128	0.132	0.123	-0.026	0.254	0.492*	-0.038	0.145	0.078
	(0.130)	(0.166)	(0.188)	(0.194)	(0.182)	(0.272)	(0.141)	(0.283)	(0.144)
Intercept	3.75	3.62	3.89	3.83	3.66	3.27	3.88	3.72	3.81
Panel E: High school curriculum was a good fit for own abilities									
STEM	-0.123	0.199	-0.446***	-0.085	-0.151	0.213	-0.364**	0.152	-0.292*
	(0.118)	(0.143)	(0.164)	(0.182)	(0.161)	(0.250)	(0.140)	(0.246)	(0.157)
Intercept	3.49	3.36	3.63	3.41	3.51	3.21	3.65	3.29	3.57
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612

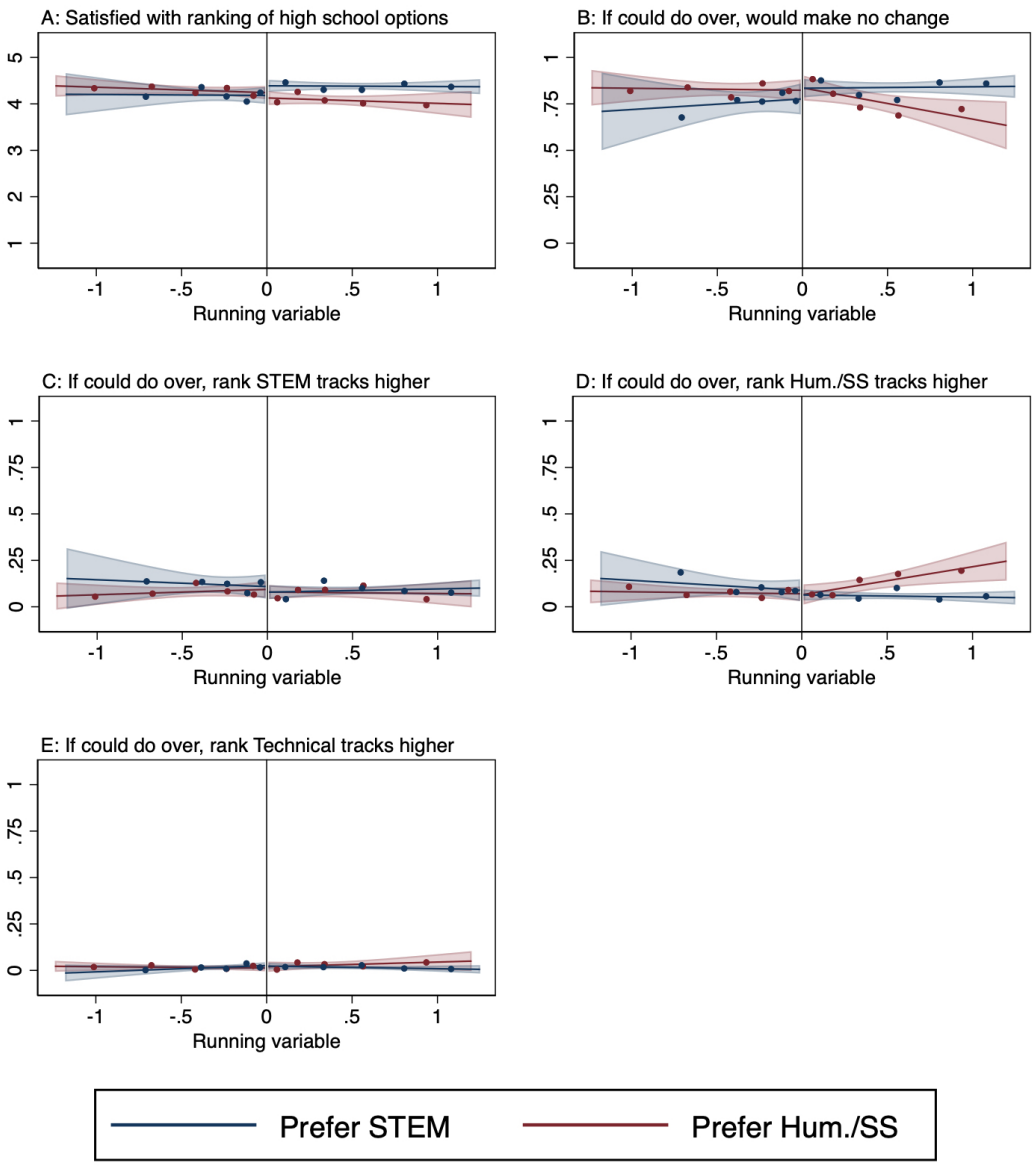
The table shows heterogeneity for the results in Panel B of Table 11. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A36: Robustness for effects on regret over high school application choices one year after high school

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: Satisfied with ranking of high school options						
STEM	0.049	0.115	0.077	0.059	0.043	0.046
	(0.129)	(0.147)	(0.133)	(0.126)	(0.121)	(0.129)
Panel B: If could do over, would make no change						
STEM	0.045	0.044	0.025	0.043	0.043	0.047
	(0.042)	(0.058)	(0.047)	(0.041)	(0.042)	(0.041)
Panel C: If could do over, would rank STEM tracks higher						
STEM	-0.032	-0.030	-0.025	-0.029	-0.023	-0.033
	(0.035)	(0.045)	(0.037)	(0.033)	(0.033)	(0.034)
Panel D: If could do over, would rank Hum./SS tracks higher						
STEM	-0.018	-0.018	-0.006	-0.021	-0.030	-0.017
	(0.032)	(0.038)	(0.032)	(0.031)	(0.031)	(0.032)
Panel E: If could do over, would rank Technical tracks higher						
STEM	0.005	0.005	0.005	0.007	0.010	0.004
	(0.013)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159

The table shows robustness for the results in Table 12. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A13: Graphical depiction of effects on regret over high school application choices one year after high school



The figure plots RD treatment effects for the outcomes in Table A36.

Table A37: Heterogeneity for effects on regret over high school application choices one year after high school

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Satisfied with ranking of high school options									
STEM	0.049	0.282	-0.185	0.215	-0.172	-0.049	0.112	-0.452**	0.265
	(0.129)	(0.189)	(0.155)	(0.219)	(0.191)	(0.189)	(0.156)	(0.183)	(0.172)
Intercept	4.20	4.14	4.25	3.99	4.31	4.27	4.16	4.48	4.06
Panel B: If could do over, would make no change									
STEM	0.045	0.081	0.009	0.063	0.122**	0.066	0.042	-0.015	0.093
	(0.042)	(0.054)	(0.057)	(0.076)	(0.060)	(0.100)	(0.047)	(0.068)	(0.062)
Intercept	0.80	0.77	0.83	0.78	0.78	0.79	0.80	0.80	0.81
Panel C: If could do over, would rank STEM tracks higher									
STEM	-0.032	-0.042	-0.022	-0.021	-0.062	-0.047	-0.028	0.034	-0.053
	(0.035)	(0.047)	(0.047)	(0.062)	(0.043)	(0.072)	(0.042)	(0.036)	(0.051)
Intercept	0.10	0.11	0.10	0.12	0.09	0.13	0.11	0.06	0.10
Panel D: If could do over, would rank Hum./SS tracks higher									
STEM	-0.018	-0.037	0.001	-0.079	-0.032	-0.049	-0.007	-0.003	-0.052
	(0.032)	(0.040)	(0.047)	(0.051)	(0.051)	(0.074)	(0.035)	(0.057)	(0.042)
Intercept	0.08	0.09	0.06	0.11	0.10	0.09	0.07	0.09	0.08
Panel E: If could do over, would rank Technical tracks higher									
STEM	0.005	-0.002	0.012	0.037*	-0.028	0.031*	-0.007	-0.016	0.012
	(0.013)	(0.015)	(0.018)	(0.020)	(0.025)	(0.016)	(0.022)	(0.045)	(0.009)
Intercept	0.02	0.03	0.01	-0.00	0.03	-0.00	0.02	0.05	0.01
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612

The table shows heterogeneity for the results in Table 12. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A38: Effects on college satisfaction and curricular fit one year after high school with no imputations for missing responses

	Like the:				**Curriculum is good fit**	**Well prepared**
	Experience	Curriculum	Peers	Instructors		
STEM	-0.462***	-0.222*	-0.455**	-0.386***	0.163	0.678***
	(0.156)	(0.133)	(0.178)	(0.142)	(0.106)	(0.153)
Intercept	2.40	2.50	2.39	2.54	3.97	2.80
Std. dev.	1.13	1.06	1.22	1.12	0.79	1.30
Cutoffs	171	171	171	171	171	171
Students	865	865	865	865	865	865
Student-cutoffs	965	965	965	965	965	965

The table is analogous to the first six columns of Table 13, but it does not impute values of 1 for students for whom the relevant questions were not asked (those who had never attended college at the time of the follow-up survey).

Table A39: Effects on regret over college application choices one year after high school with no imputations for missing responses

	Satisfied with ranking	**If could do over, would:**		
		Make no change	Rank a different college higher	Rank a different subject higher
STEM	0.226*	0.099*	-0.099**	-0.001
	(0.136)	(0.056)	(0.043)	(0.035)
Intercept	4.26	0.79	0.16	0.06
Std. dev.	0.92	0.37	0.26	0.29
Cutoffs	171	171	171	171
Students	865	865	865	865
Student-cutoffs	965	965	965	965

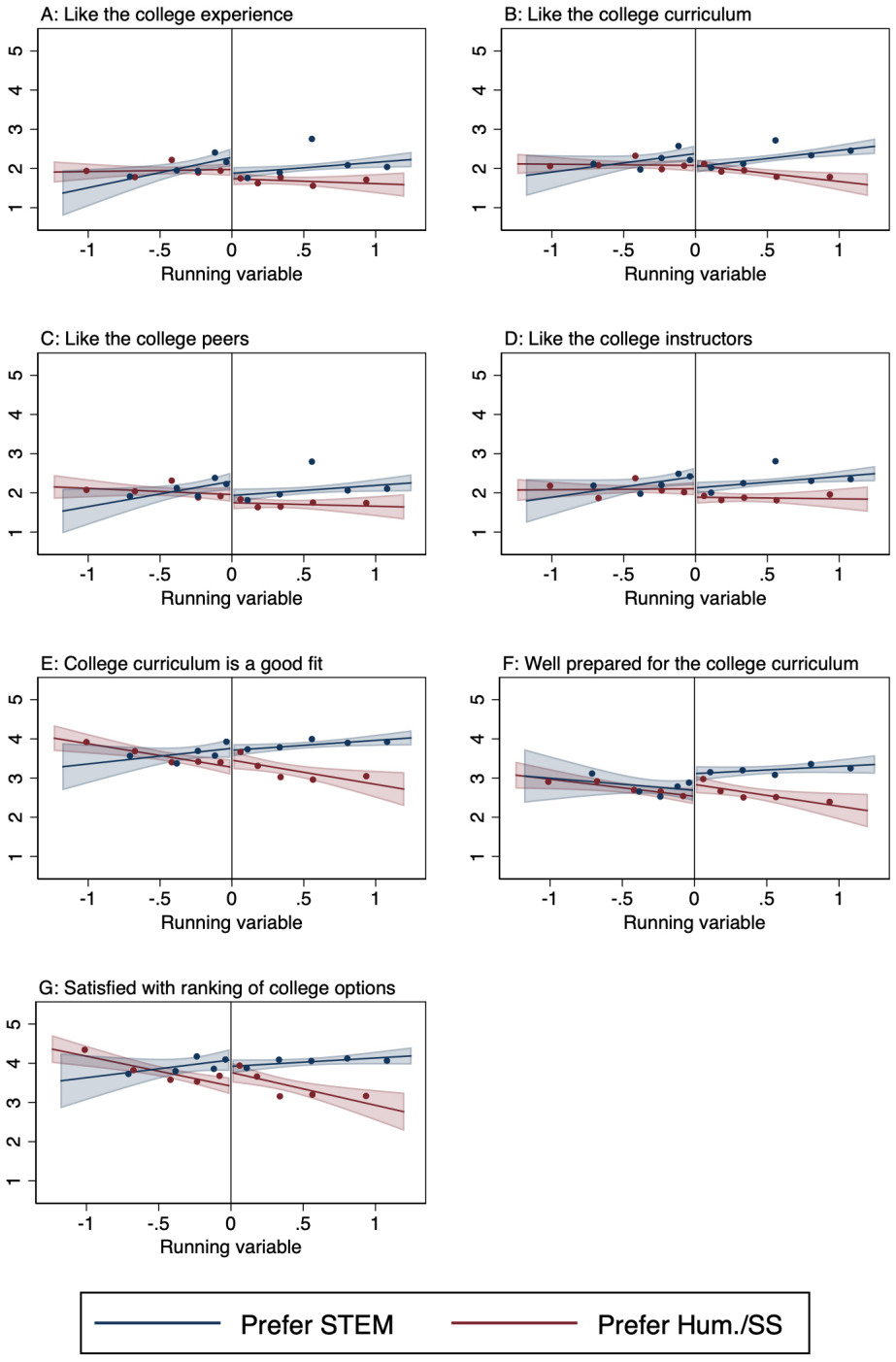
The table shows effects on regret over college application choices from the follow-up survey. Variables are available only for students who ever attended college. The first column is analogous to the seventh column of Table 13, but it does not impute values of 1 for students for whom the question was not asked (those who had never attended college at the time of the follow-up survey).

Table A40: Robustness for effects on college satisfaction, curricular fit, and regret one year after high school

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: Like the college experience						
STEM	-0.443***	-0.653***	-0.498***	-0.420***	-0.384***	-0.450***
	(0.138)	(0.161)	(0.150)	(0.134)	(0.131)	(0.140)
Panel B: Like the college curriculum						
STEM	-0.227*	-0.297**	-0.266**	-0.211*	-0.161	-0.238*
	(0.129)	(0.149)	(0.130)	(0.121)	(0.118)	(0.131)
Panel C: Like the college peers						
STEM	-0.398**	-0.502**	-0.382**	-0.430***	-0.382**	-0.402**
	(0.166)	(0.196)	(0.173)	(0.156)	(0.150)	(0.169)
Panel D: Like the college instructors						
STEM	-0.352***	-0.547***	-0.409***	-0.320**	-0.290**	-0.365***
	(0.134)	(0.154)	(0.136)	(0.128)	(0.124)	(0.137)
Panel E: College curriculum is a good fit for own abilities						
STEM	0.082	0.067	0.141	0.054	0.097	0.079
	(0.156)	(0.183)	(0.159)	(0.148)	(0.148)	(0.159)
Panel F: Well prepared for the college curriculum						
STEM	0.490***	0.494***	0.524***	0.448***	0.417***	0.489***
	(0.156)	(0.183)	(0.164)	(0.154)	(0.151)	(0.158)
Panel G: Satisfied with ranking of college options						
STEM	0.122	0.090	0.169	0.091	0.097	0.125
	(0.179)	(0.212)	(0.183)	(0.174)	(0.172)	(0.182)
Cutoffs	190	160	181	201	208	190
Students	1,046	786	933	1,145	1,199	1,046
Student-cutoffs	1,159	886	1,041	1,263	1,319	1,159

The table shows robustness for the results in Table 13. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A14: Graphical depiction of effects on college satisfaction, curricular fit, and regret one year after high school



The figure plots RD treatment effects for the outcomes in Table A40.

Table A41: Heterogeneity for effects on college satisfaction, curricular fit, and regret one year after high school

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Like the college experience									
STEM	-0.443***	-0.521***	-0.366**	-0.746***	-0.213	-0.496**	-0.477***	-0.441	-0.413**
	(0.138)	(0.188)	(0.166)	(0.192)	(0.227)	(0.246)	(0.167)	(0.320)	(0.172)
Intercept	2.20	2.34	2.05	2.52	1.95	2.10	2.30	2.13	2.26
Panel B: Like the college curriculum									
STEM	-0.227*	-0.433**	-0.021	-0.543**	-0.064	-0.224	-0.188	-0.324	-0.205
	(0.129)	(0.165)	(0.176)	(0.215)	(0.178)	(0.235)	(0.169)	(0.303)	(0.137)
Intercept	2.25	2.39	2.11	2.72	1.95	2.24	2.23	2.23	2.33
Panel C: Like the college peers									
STEM	-0.398**	-0.470**	-0.326	-0.515*	-0.262	-0.319	-0.453**	-0.574	-0.348*
	(0.166)	(0.215)	(0.219)	(0.291)	(0.218)	(0.301)	(0.182)	(0.368)	(0.203)
Intercept	2.18	2.36	2.00	2.49	1.89	2.05	2.27	2.32	2.16
Panel D: Like the college instructors									
STEM	-0.352***	-0.376**	-0.328*	-0.353	-0.386*	-0.131	-0.443***	-0.303	-0.345**
	(0.134)	(0.169)	(0.192)	(0.233)	(0.221)	(0.259)	(0.158)	(0.281)	(0.160)
Intercept	2.31	2.44	2.17	2.58	2.16	2.12	2.40	2.11	2.44
Panel E: College curriculum is a good fit for own abilities									
STEM	0.082	-0.052	0.216	0.200	-0.040	-0.157	0.031	-0.454*	0.206
	(0.156)	(0.205)	(0.223)	(0.271)	(0.239)	(0.342)	(0.201)	(0.240)	(0.174)
Intercept	3.48	3.75	3.21	3.61	3.37	3.55	3.57	3.59	3.74
Panel F: Well prepared for the college curriculum									
STEM	0.490***	0.569**	0.410**	0.623**	0.364	0.660**	0.279	-0.142	0.663***
	(0.156)	(0.241)	(0.182)	(0.258)	(0.269)	(0.288)	(0.205)	(0.293)	(0.203)
Intercept	2.50	2.55	2.45	2.65	2.41	2.31	2.67	2.70	2.73
Panel G: Satisfied with ranking of college options									
STEM	0.122	-0.207	0.451**	0.368	0.021	0.282	0.022	-0.215	0.198
	(0.179)	(0.267)	(0.212)	(0.269)	(0.273)	(0.364)	(0.230)	(0.275)	(0.220)
Intercept	3.72	4.14	3.31	3.79	3.59	3.49	3.86	3.61	4.05
Cutoffs	190	96	94	117	120	92	147	104	86
Students	1,046	589	570	490	476	303	676	525	545
Student-cutoffs	1,159	589	570	546	520	325	746	547	612

The table shows heterogeneity for the results in Table 13. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

A9 Additional results for effects on other outcomes

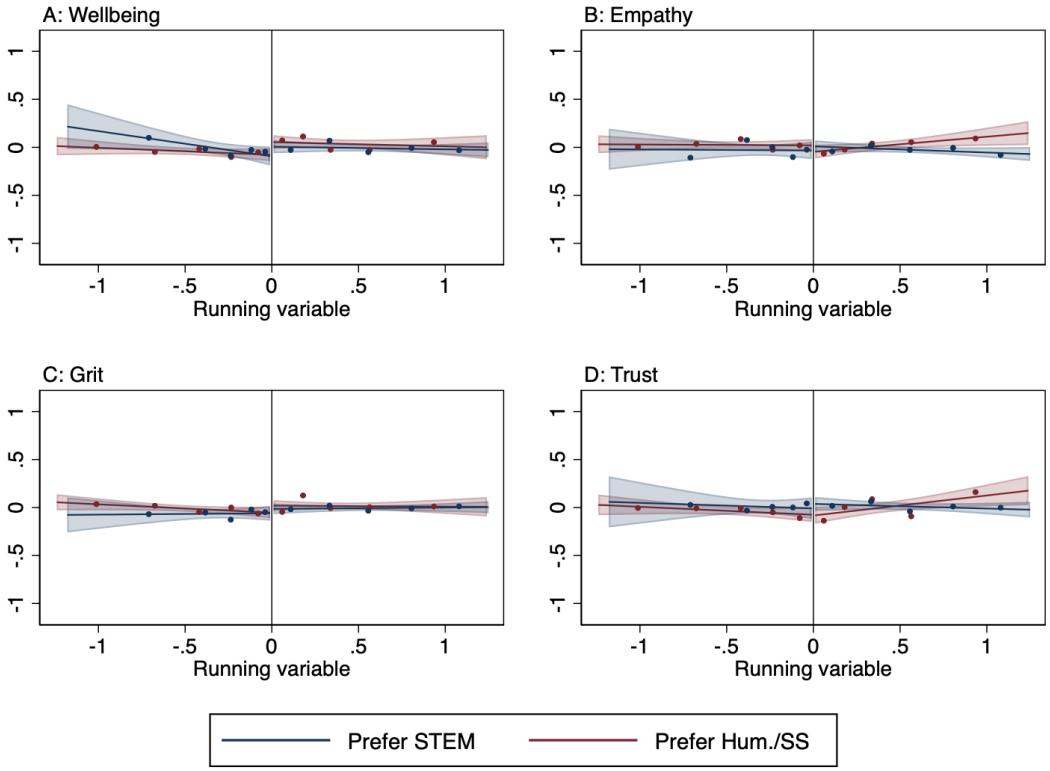
A9.1 Outcomes measured at the end of high school

Table A42: Robustness for effects on pyschological outcomes

	Main	**Alternative bandwidths**				**Adding covariates**
		0.75	1.00	1.50	1.75	
Panel A: Wellbeing						
STEM	0.134***	0.123**	0.145***	0.144***	0.129***	0.125**
	(0.051)	(0.057)	(0.052)	(0.047)	(0.045)	(0.050)
Panel B: Empathy						
STEM	-0.012	-0.040	-0.033	-0.029	-0.013	0.001
	(0.042)	(0.052)	(0.047)	(0.040)	(0.039)	(0.042)
Panel C: Grit						
STEM	0.068*	0.083**	0.073*	0.076**	0.078**	0.072**
	(0.036)	(0.042)	(0.037)	(0.034)	(0.033)	(0.036)
Panel D: Trust						
STEM	0.026	0.019	0.008	0.024	0.009	0.026
	(0.051)	(0.058)	(0.054)	(0.049)	(0.049)	(0.050)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987

The table shows robustness for the results in Table 14. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A15: Graphical depiction of effects on psychological outcomes



The figure plots RD treatment effects for the outcomes in Table A42.

Table A43: Effects on components of the wellbeing index

	Wellbeing	**Overall, am happy**	**Belong at school**	**Not depressed**
STEM	0.134***	0.146**	0.199**	0.066
	(0.051)	(0.072)	(0.077)	(0.055)
Intercept	-0.10	3.66	2.58	2.67
Std. dev.	0.74	1.05	1.12	0.78
Cutoffs	293	293	293	293
Students	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987

The table shows effects on the components of the wellbeing index in Table 14. Wellbeing is the index and is calculated as the average of standardized values of the three components. "Overall, am happy" and "Belong at school" are both on a scale of 1-5. "Not depressed" is the average from a 4-question depression questionnaire. The questions in the questionnaire are one a four point scale. In calculating, "Not depressed" we order the responses such that higher values mean lower depression.

Table A44: Effects on components of the empathy index

	Empathy	**Prefer characters to plots**	**Notice people's emotions**
STEM	-0.012	0.104	-0.094*
	(0.042)	(0.076)	(0.055)
Intercept	-0.01	2.73	4.40
Std. dev.	0.70	1.28	0.89
Cutoffs	293	293	293
Students	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987

The table shows effects on the components of the empathy index in Table 14. Empathy is the index and is calculated as the average of standardized values of the two components. "Prefer characters to plots" and "Notice emotions" are both on a scale of 1-5. The associated statements are: "I prefer books and movies with exciting plots to those that focus on the feelings and motivations of the characters" and "I notice when people are sad or angry even when they try to hide it". In calculating, "Prefer characters to plots", we reverse the order of the responses to the associated statement.

Table A45: Effects on components of the grit index

	Grit	**Trade now for later**	**Finish what begin**	**Am a hard worker**	**Don't get distracted**	**Follow through with goals**
STEM	0.068*	-0.017	0.133**	0.121*	0.158*	-0.023
	(0.036)	(0.074)	(0.063)	(0.065)	(0.081)	(0.091)
Intercept	-0.07	3.85	3.53	3.70	2.50	3.11
Std. dev.	0.61	1.14	1.10	1.03	1.21	1.31
Cutoffs	293	293	293	293	293	293
Students	3,562	3,562	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987	3,987	3,987

The table shows effects on the components of the grit index in Table 14. Grit is the index and is calculated as the average of standardized values of the five components. The components are all on a scale of 1-5. The associated statements are, respectively, "I am willing to give up something that is beneficial for me today in order to benefit more in the future", "I finish whatever I begin", "I am a hard worker", "New ideas and projects sometimes distract me from previous ones", and "I often set a goal but later choose to pursue a different one". In calculating "Don't get distracted" and "Follow through with goals", we reverse the order of the reponses to the associated statements.

Table A46: Effects on components of the trust index

	Trust	**Can trust:**	
		Most people	Gov. workers
STEM	0.026	0.009	0.044
	(0.051)	(0.066)	(0.068)
Intercept	-0.05	2.10	2.09
Std. dev.	0.83	1.07	1.02
Cutoffs	293	293	293
Students	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987

The table shows effects on the components of the trust index in Table 14. Trust is the index and is calculated as the average of standardized values of the two components. The components are all on a scale of 1-5. The associated statements are, "Generally speaking, most people can be trusted" and "Generally speaking, government workers can be trusted".

Table A47: Heterogeneity for effects on pyschological outcomes

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Wellbeing									
STEM	0.134***	0.111	0.156***	0.193**	0.082	0.056	0.143**	0.095	0.115
	(0.051)	(0.077)	(0.053)	(0.077)	(0.077)	(0.088)	(0.068)	(0.085)	(0.077)
Intercept	-0.10	-0.10	-0.09	-0.11	-0.05	0.04	-0.16	-0.02	-0.12
Panel B: Empathy									
STEM	-0.012	0.049	-0.073*	-0.007	-0.048	-0.035	-0.013	0.012	0.009
	(0.042)	(0.062)	(0.044)	(0.070)	(0.065)	(0.082)	(0.056)	(0.083)	(0.062)
Intercept	-0.01	-0.03	0.02	-0.07	0.07	-0.06	0.04	0.02	-0.08
Panel C: Grit									
STEM	0.068*	0.051	0.084*	0.067	0.057	0.128**	0.026	0.064	0.047
	(0.036)	(0.044)	(0.048)	(0.062)	(0.052)	(0.061)	(0.051)	(0.051)	(0.054)
Intercept	-0.07	-0.06	-0.07	-0.08	-0.03	-0.12	-0.02	-0.08	-0.02
Panel D: Trust									
STEM	0.026	0.053	-0.002	0.013	0.004	-0.024	0.052	-0.029	0.018
	(0.051)	(0.065)	(0.066)	(0.080)	(0.078)	(0.088)	(0.071)	(0.080)	(0.082)
Intercept	-0.05	-0.01	-0.09	0.00	-0.06	0.07	-0.13	0.04	-0.07
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894

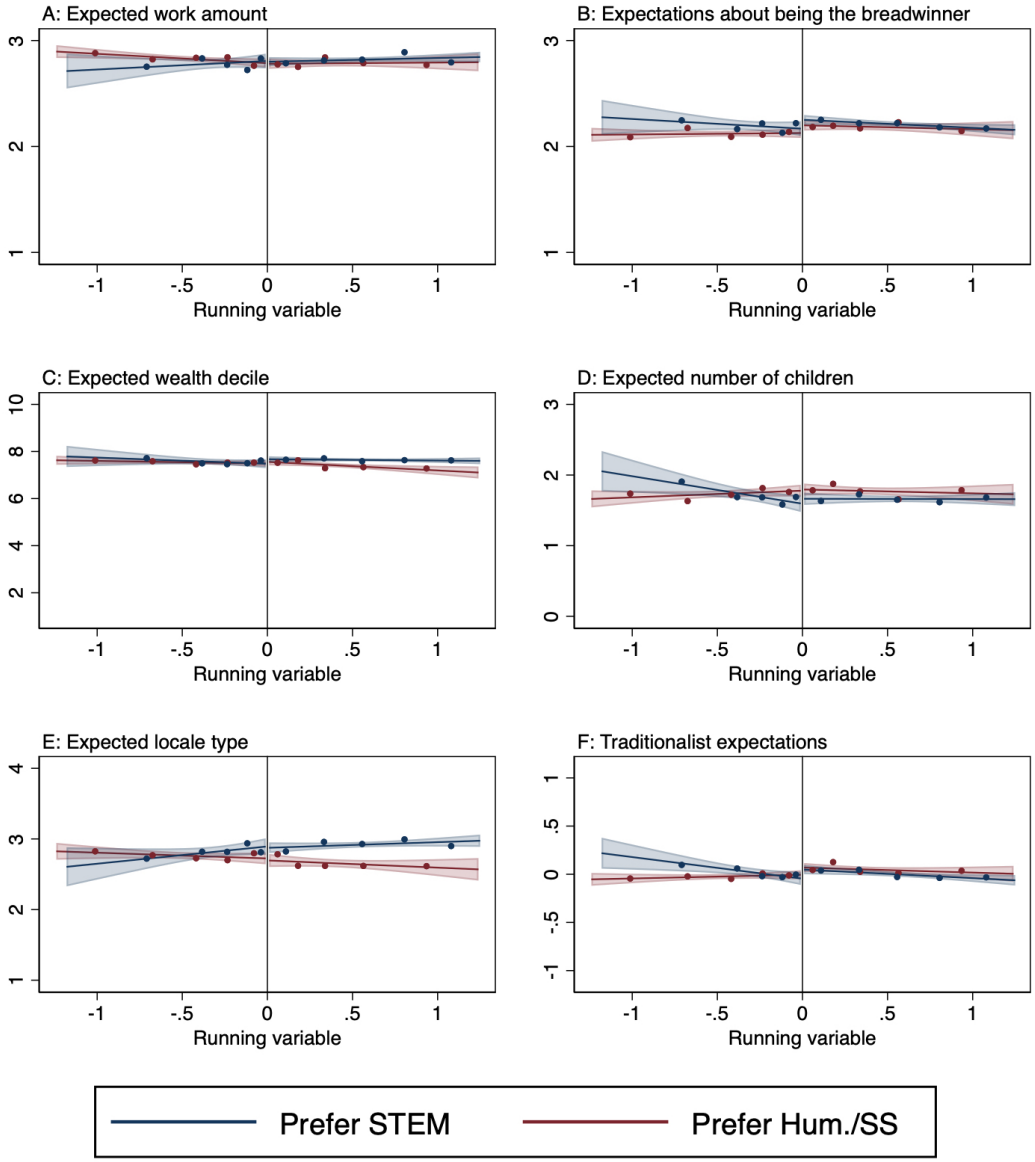
The table shows heterogeneity for the results in Table 14. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A48: Robustness for effects on expectations

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: Expected work amount						
STEM	-0.009	-0.025	-0.011	-0.022	-0.016	-0.002
	(0.030)	(0.037)	(0.033)	(0.029)	(0.027)	(0.030)
Panel B: Expectations about being the breadwinner						
STEM	0.091***	0.089**	0.106***	0.096***	0.092***	0.066**
	(0.035)	(0.039)	(0.037)	(0.033)	(0.033)	(0.031)
Panel C: Expected wealth decile						
STEM	0.140	0.187*	0.127	0.133	0.118	0.137
	(0.090)	(0.112)	(0.099)	(0.087)	(0.084)	(0.090)
Panel D: Expected number of children						
STEM	0.048	0.076	0.055	0.041	0.029	0.042
	(0.063)	(0.077)	(0.069)	(0.060)	(0.058)	(0.063)
Panel E: Expected locale type						
STEM	-0.032	-0.012	-0.007	-0.048	-0.040	-0.021
	(0.057)	(0.066)	(0.059)	(0.056)	(0.054)	(0.055)
Panel F: Traditionalist expectations						
STEM	0.098***	0.132***	0.106***	0.106***	0.080**	0.058**
	(0.035)	(0.040)	(0.037)	(0.034)	(0.033)	(0.026)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987

The table shows robustness for the results in Table 15. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A16: Graphical depiction of effects on expectations



The figure plots RD treatment effects for the outcomes in Table A16.

Table A49: Heterogeneity for effects on expectations

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Expected work amount									
STEM	-0.009	-0.009	-0.009	0.025	-0.071*	0.035	-0.026	0.026	-0.031
	(0.030)	(0.042)	(0.034)	(0.052)	(0.042)	(0.064)	(0.036)	(0.050)	(0.042)
Intercept	2.79	2.80	2.78	2.79	2.80	2.72	2.83	2.74	2.84
Panel B: Expectations about being the breadwinner									
STEM	0.091***	0.095**	0.087**	0.112*	0.096**	0.150**	0.014	0.092*	0.071
	(0.035)	(0.047)	(0.044)	(0.060)	(0.048)	(0.064)	(0.035)	(0.051)	(0.056)
Intercept	2.15	2.17	2.12	2.18	2.10	2.34	2.04	2.16	2.15
Panel C: Expected wealth decile									
STEM	0.140	0.217*	0.062	0.046	0.258*	0.062	0.159	0.182	0.117
	(0.090)	(0.116)	(0.116)	(0.147)	(0.139)	(0.159)	(0.118)	(0.166)	(0.142)
Intercept	7.48	7.46	7.50	7.62	7.39	7.56	7.43	7.37	7.61
Panel D: Expected number of children									
STEM	0.048	0.077	0.020	0.081	0.087	0.173*	0.006	0.056	0.033
	(0.063)	(0.097)	(0.068)	(0.100)	(0.079)	(0.101)	(0.076)	(0.097)	(0.092)
Intercept	1.69	1.59	1.79	1.72	1.66	1.65	1.68	1.74	1.66
Panel E: Expected locale type									
STEM	-0.032	-0.022	-0.042	-0.007	-0.110	-0.076	-0.010	-0.012	-0.014
	(0.057)	(0.074)	(0.071)	(0.090)	(0.080)	(0.116)	(0.070)	(0.103)	(0.076)
Intercept	2.81	2.89	2.72	2.83	2.82	2.81	2.84	2.64	2.93
Panel F: Traditionalist expectations									
STEM	0.098***	0.106**	0.089**	0.108**	0.156***	0.129***	0.026	0.086	0.092**
	(0.035)	(0.051)	(0.039)	(0.053)	(0.043)	(0.050)	(0.034)	(0.060)	(0.046)
Intercept	-0.03	-0.05	-0.00	0.06	-0.10	0.29	-0.22	0.03	-0.05
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894

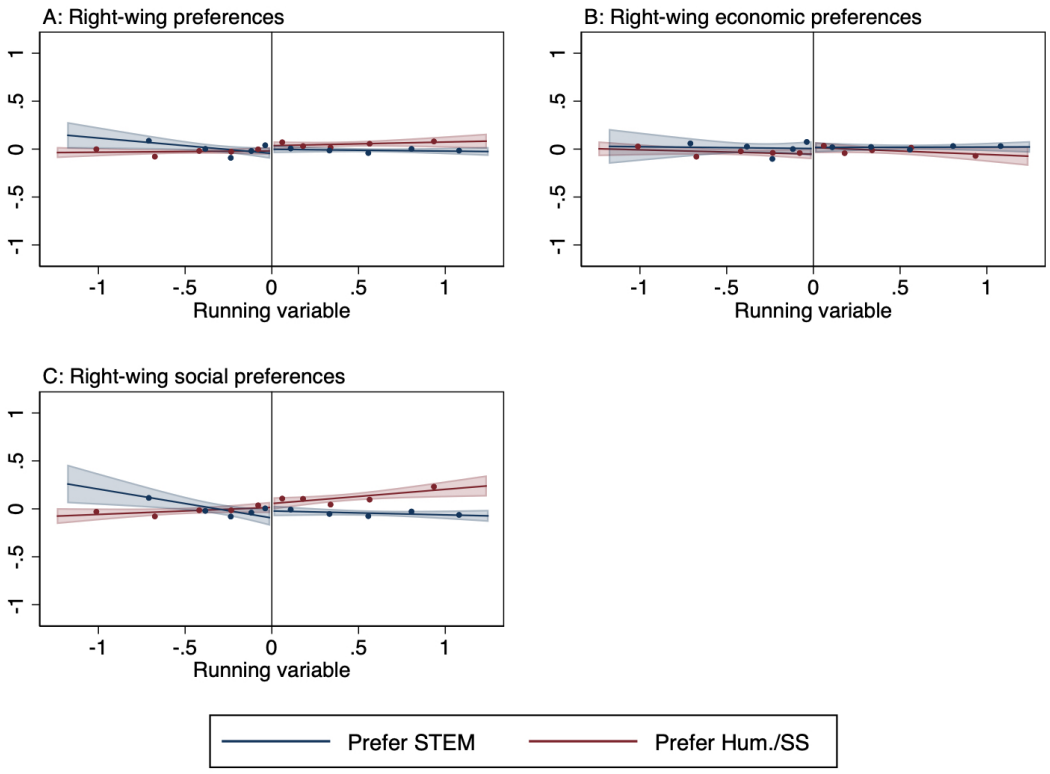
The table shows heterogeneity for the results in Table 15. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A50: Robustness for effects on political preferences

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: Right-wing preferences						
STEM	0.058*	0.041	0.065*	0.061**	0.058**	0.049
	(0.031)	(0.039)	(0.033)	(0.030)	(0.029)	(0.031)
Panel B: Right-wing economic preferences						
STEM	0.045	0.033	0.051	0.044	0.037	0.039
	(0.041)	(0.048)	(0.043)	(0.040)	(0.038)	(0.041)
Panel C: Right-wing social preferences						
STEM	0.070*	0.049	0.078*	0.077**	0.079**	0.060
	(0.040)	(0.052)	(0.044)	(0.038)	(0.037)	(0.040)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987

The table shows robustness for the results in Table 16. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A17: Graphical depiction of effects on political preferences



The figure plots RD treatment effects for the outcomes in Table A50.

Table A51: Effects on components of the political preferences indices

	Right-wing economic preferences				**Right-wing social preferences**			
	Index	The poor are lazy	Redistribution is bad	Meritocracy is good	Index	Tradition is good	Wife earning more is a problem	Divorce is immoral
Panel A: All students								
STEM	0.045	0.073	-0.022	0.030	0.070*	0.065	0.029	0.149**
	(0.041)	(0.087)	(0.089)	(0.024)	(0.040)	(0.068)	(0.080)	(0.073)
Intercept	-0.02	2.42	3.13	0.54	-0.05	3.75	1.84	1.72
Std. dev.	0.59	1.19	1.26	0.33	0.64	1.12	1.21	1.16
Cutoffs	293	293	293	293	293	293	293	293
Students	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562
Student-cutoffs	3,987	3,987	3,987	3,987	3,987	3,987	3,987	3,987
Panel B: Male students								
STEM	0.223***	0.298**	0.077	0.118***	0.068	0.062	0.114	0.062
	(0.067)	(0.138)	(0.161)	(0.038)	(0.076)	(0.130)	(0.140)	(0.119)
Intercept	-0.07	2.55	3.05	0.48	0.03	3.75	1.86	1.97
Std. dev.	0.60	1.20	1.27	0.33	0.67	1.16	1.24	1.21
Cutoffs	206	206	206	206	206	206	206	206
Students	1,251	1,251	1,251	1,251	1,251	1,251	1,251	1,251
Student-cutoffs	1,396	1,396	1,396	1,396	1,396	1,396	1,396	1,396
Panel C: Female students								
STEM	-0.055	-0.096	-0.062	-0.012	0.077	0.060	0.014	0.196**
	(0.048)	(0.108)	(0.108)	(0.029)	(0.050)	(0.089)	(0.097)	(0.098)
Intercept	-0.01	2.34	3.15	0.57	-0.11	3.75	1.80	1.53
Std. dev.	0.58	1.16	1.25	0.34	0.62	1.10	1.18	1.09
Cutoffs	253	253	253	253	253	253	253	253
Students	2,254	2,254	2,254	2,254	2,254	2,254	2,254	2,254
Student-cutoffs	2,510	2,510	2,510	2,510	2,510	2,510	2,510	2,510

The table shows effects on the components of the economic and social preferences indices in Table 15. The columns labelled "Index" are the indices. The other columns are the component variables. The indices are averages of standardized values of the component variables. All variables except "Meritocrocy is good" are on a scale of 1-5. "Meritocrocacy is good" is the average of three yes or no questions about splitting students between classes based on academic ability. The questions are whether the student agrees that this is fair, that it does not stigmatize students, and that it improves learning. The overall political preferences index is the average of the economic and social preferences indices. This is equal to the average of standardized values of the six component variables.

Table A52: Heterogeneity for effects on political preferences

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Right-wing preferences									
STEM	0.058*	0.047	0.069*	0.089*	0.059	0.145***	0.011	0.051	0.045
	(0.031)	(0.046)	(0.035)	(0.050)	(0.044)	(0.054)	(0.036)	(0.051)	(0.043)
Intercept	-0.04	-0.05	-0.02	-0.05	-0.01	-0.02	-0.06	0.02	-0.07
Panel B: Right-wing economic preferences									
STEM	0.045	0.012	0.078	0.034	0.088	0.223***	-0.055	0.028	0.042
	(0.041)	(0.059)	(0.048)	(0.066)	(0.066)	(0.067)	(0.048)	(0.060)	(0.058)
Intercept	-0.02	0.01	-0.06	0.01	-0.05	-0.07	-0.01	0.01	-0.04
Panel C: Right-wing social preferences									
STEM	0.070*	0.081	0.059	0.144**	0.030	0.068	0.077	0.074	0.048
	(0.040)	(0.059)	(0.046)	(0.061)	(0.055)	(0.076)	(0.050)	(0.073)	(0.058)
Intercept	-0.05	-0.10	0.01	-0.10	0.03	0.03	-0.11	0.04	-0.10
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894

The table shows heterogeneity for the results in Table 16. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A53: Effects on turnout and political preferences from the second follow-up survey

	Plan to turn out to vote	**Boys are naturally better in math**	**Climate change is one of the most serious issues**
Panel A: All students			
STEM	0.027	-0.214	0.147
	(0.036)	(0.161)	(0.156)
Intercept	0.87	2.81	3.24
Std. dev.	0.26	1.22	1.20
Cutoffs	198	197	197
Students	1,089	1,087	1,081
Student-cutoffs	1,199	1,197	1,190
Panel B: Male students			
STEM	-0.005	0.034	-0.010
	(0.077)	(0.287)	(0.295)
Intercept	0.89	2.76	3.39
Std. dev.	0.28	1.18	1.27
Cutoffs	101	101	101
Students	350	350	349
Student-cutoffs	373	373	372
Panel C: Female students			
STEM	0.049	-0.415**	0.359**
	(0.043)	(0.205)	(0.179)
Intercept	0.87	2.83	3.15
Std. dev.	0.24	1.23	1.16
Cutoffs	143	143	142
Students	665	665	659
Student-cutoffs	728	728	721

The table shows effects on the political variables from the second follow-up survey. "Plan to turn out to vote" is the average of responses from two questions asking if respondents planned to vote in the upcoming presidential and parliamentary elections. The values for these variables are 0 for no, 0.5 for maybe, and 1 for yes. The other columns are on a scale of 1 to 5, where 1 is disagree strongly and 5 is agree strongly.

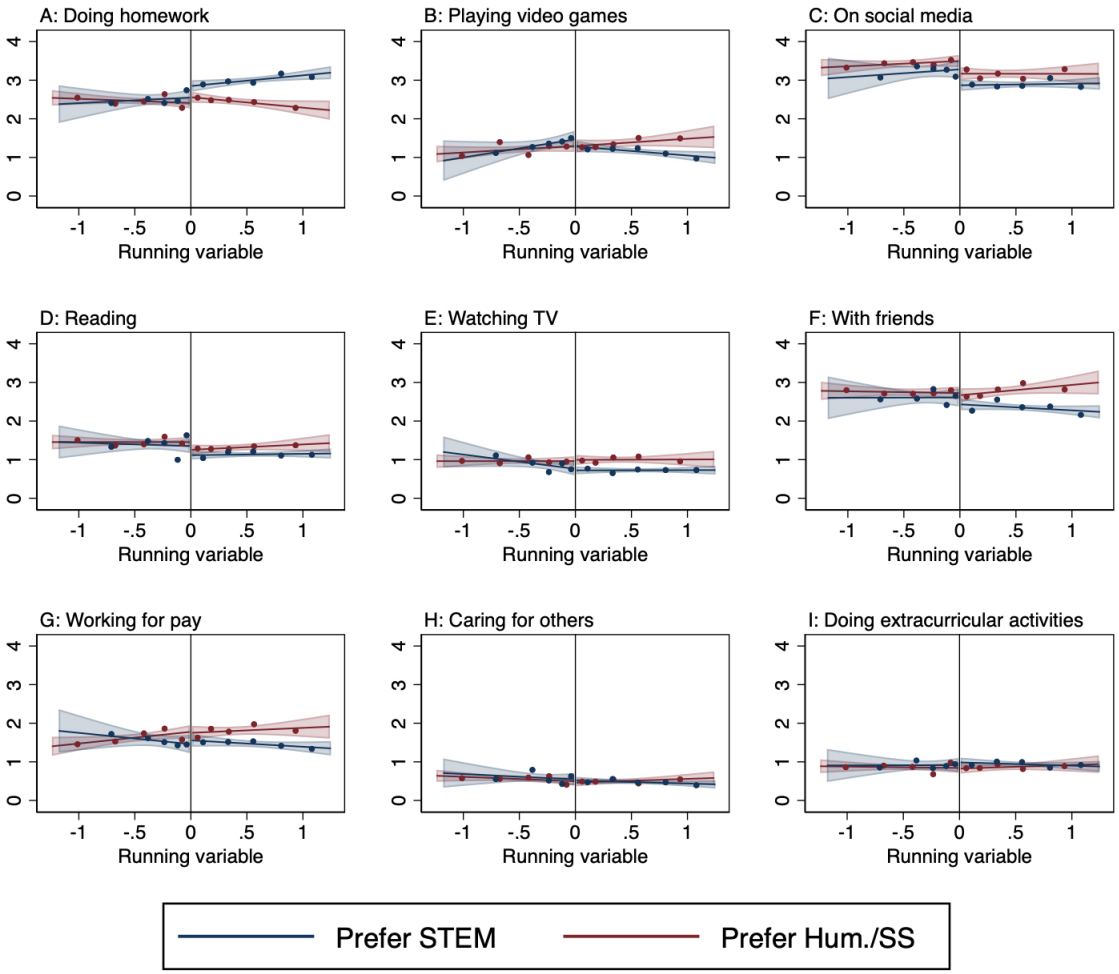
A9.2 Mechanisms for end-of-high-school effects on other outcomes

Table A54: Robustness for effects on time use on a typical weekday

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: Doing homework						
STEM	0.248**	0.193	0.203*	0.276***	0.305***	0.297***
	(0.109)	(0.126)	(0.118)	(0.105)	(0.103)	(0.103)
Panel B: Playing video games						
STEM	-0.096	-0.058	-0.084	-0.064	-0.071	-0.195**
	(0.107)	(0.134)	(0.119)	(0.102)	(0.098)	(0.097)
Panel C: On social media						
STEM	-0.428***	-0.290**	-0.403***	-0.426***	-0.406***	-0.387***
	(0.111)	(0.136)	(0.118)	(0.104)	(0.102)	(0.113)
Panel D: Reading						
STEM	-0.251***	-0.386***	-0.294***	-0.247***	-0.235***	-0.218**
	(0.091)	(0.114)	(0.098)	(0.086)	(0.083)	(0.089)
Panel E: Watching TV						
STEM	-0.004	-0.009	0.044	-0.018	-0.061	0.008
	(0.074)	(0.077)	(0.079)	(0.071)	(0.069)	(0.073)
Panel F: With friends						
STEM	-0.127	-0.136	-0.144	-0.128	-0.143	-0.131
	(0.112)	(0.129)	(0.119)	(0.106)	(0.102)	(0.113)
Panel G: Working for pay						
STEM	0.047	0.063	0.098	0.070	0.113	0.040
	(0.114)	(0.134)	(0.119)	(0.108)	(0.106)	(0.114)
Panel H: Caring for others						
STEM	-0.036	-0.021	0.006	-0.048	-0.047	-0.022
	(0.058)	(0.067)	(0.060)	(0.059)	(0.058)	(0.058)
Panel I: Doing extracurricular activities						
STEM	0.032	0.025	0.048	0.046	0.028	0.032
	(0.086)	(0.096)	(0.092)	(0.082)	(0.076)	(0.083)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987

The table shows robustness for the results in Table 17. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A18: Graphical depiction of effects on time use on a typical weekday



The figure plots RD treatment effects for the outcomes in Table A54.

Table A55: Heterogeneity for effects on time use on a typical weekday

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Doing homework									
STEM	0.248**	0.331**	0.165	0.308*	0.172	0.342*	0.404***	0.490**	0.058
	(0.109)	(0.157)	(0.123)	(0.175)	(0.150)	(0.185)	(0.124)	(0.192)	(0.153)
Intercept	2.44	2.48	2.41	2.46	2.45	1.86	2.66	2.13	2.75
Panel B: Playing video games									
STEM	-0.096	-0.204	0.012	0.050	-0.076	-0.362*	-0.137	0.050	-0.189
	(0.107)	(0.147)	(0.126)	(0.174)	(0.158)	(0.191)	(0.106)	(0.164)	(0.157)
Intercept	1.41	1.52	1.30	1.49	1.37	2.57	0.78	1.45	1.37
Panel C: On social media									
STEM	-0.428***	-0.462***	-0.394***	-0.453***	-0.325*	-0.215	-0.437***	-0.064	-0.560***
	(0.111)	(0.146)	(0.138)	(0.163)	(0.175)	(0.189)	(0.147)	(0.185)	(0.148)
Intercept	3.42	3.32	3.53	3.26	3.50	2.87	3.68	3.19	3.48
Panel D: Reading									
STEM	-0.251***	-0.267*	-0.235***	-0.264**	-0.280**	-0.472***	-0.103	-0.345**	-0.287**
	(0.091)	(0.139)	(0.089)	(0.131)	(0.141)	(0.153)	(0.126)	(0.163)	(0.128)
Intercept	1.42	1.38	1.46	1.29	1.57	1.17	1.59	1.60	1.35
Panel E: Watching TV									
STEM	-0.004	-0.046	0.038	0.106	-0.020	-0.050	0.037	0.094	-0.031
	(0.074)	(0.101)	(0.097)	(0.108)	(0.117)	(0.125)	(0.097)	(0.121)	(0.095)
Intercept	0.86	0.76	0.96	0.71	0.97	0.75	0.93	0.84	0.81
Panel F: With friends									
STEM	-0.127	-0.198	-0.055	-0.013	-0.040	-0.029	-0.235	0.064	-0.180
	(0.112)	(0.139)	(0.150)	(0.174)	(0.167)	(0.194)	(0.148)	(0.184)	(0.143)
Intercept	2.68	2.64	2.71	2.70	2.61	2.73	2.70	2.64	2.62
Panel G: Working for pay									
STEM	0.047	0.111	-0.017	0.278	-0.172	0.114	-0.061	0.121	0.040
	(0.114)	(0.166)	(0.123)	(0.176)	(0.172)	(0.205)	(0.158)	(0.158)	(0.176)
Intercept	1.63	1.46	1.79	1.48	1.81	1.67	1.62	1.76	1.42
Panel H: Caring for others									
STEM	-0.036	-0.032	-0.040	0.082	-0.139	0.013	-0.058	0.074	-0.075
	(0.058)	(0.076)	(0.073)	(0.086)	(0.090)	(0.087)	(0.085)	(0.082)	(0.087)
Intercept	0.53	0.56	0.49	0.41	0.59	0.41	0.58	0.43	0.56
Panel I: Doing extracurricular activities									
STEM	0.032	0.080	-0.016	0.082	0.091	0.080	0.007	0.029	0.065
	(0.086)	(0.111)	(0.108)	(0.139)	(0.113)	(0.185)	(0.100)	(0.133)	(0.138)
Intercept	0.88	0.92	0.83	0.96	0.71	1.04	0.78	0.79	0.97
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894

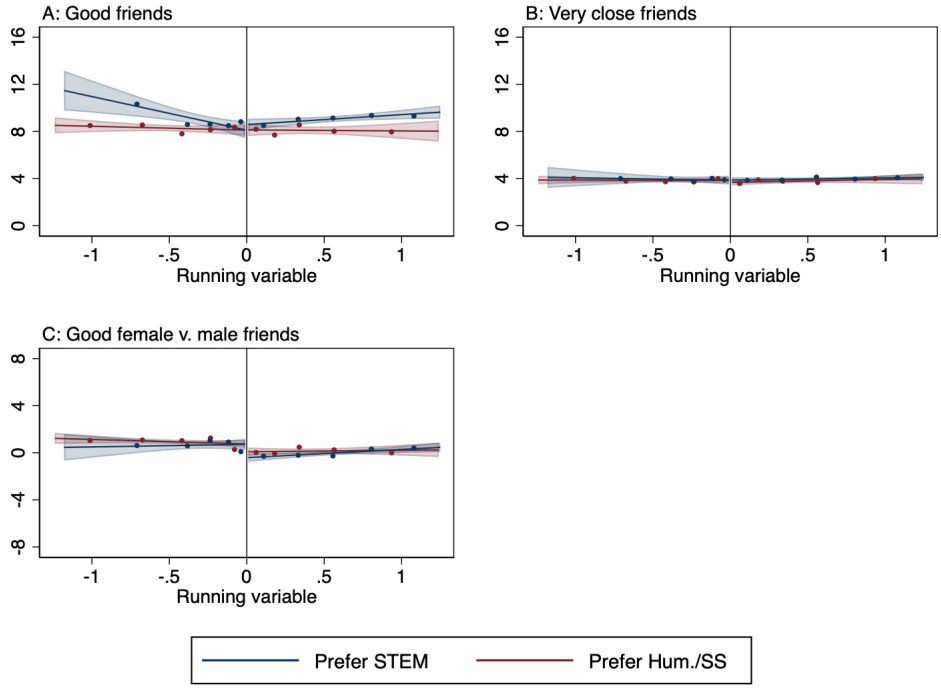
The table shows heterogeneity for the results in Table 17. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A56: Robustness for effects on friendships

	Main	Alternative bandwidths				Adding covariates
		0.75	1.00	1.50	1.75	
Panel A: Good friends						
STEM	0.255	-0.051	0.234	0.284	0.321	0.165
	(0.369)	(0.437)	(0.395)	(0.356)	(0.340)	(0.360)
Panel B: Very close friends						
STEM	-0.096	-0.130	-0.134	-0.138	-0.089	-0.143
	(0.177)	(0.199)	(0.184)	(0.168)	(0.169)	(0.173)
Panel C: Good female v. male friends						
STEM	-1.05***	-0.817***	-1.02***	-1.07***	-0.940***	-0.840***
	(0.257)	(0.298)	(0.274)	(0.241)	(0.240)	(0.222)
Cutoffs	293	266	284	299	304	293
Students	3,562	2,629	3,172	3,807	3,968	3,562
Student-cutoffs	3,987	2,993	3,573	4,249	4,415	3,987

The table shows robustness for the results in Table 18. Main is the main specification, which uses a 1.25 point bandwidth. The added covariates are the components of the transition score, an indicator for female, and mother's and father's years of schooling. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Figure A19: Graphical depiction of effects on friendships



The figure plots RD treatment effects for the outcomes in Table A56.

Table A57: Heterogeneity for effects on friendships

	All	Prefer		Stronger in		Gender		Cutoff score	
		STEM	Hum./SS	Math	Language	Male	Female	Low	High
Panel A: Good friends									
STEM	0.255	0.505	0.005	0.738	0.229	-0.158	0.158	0.602	-0.371
	(0.369)	(0.497)	(0.455)	(0.564)	(0.536)	(0.689)	(0.426)	(0.530)	(0.502)
Intercept	8.03	7.96	8.10	8.31	7.46	9.49	7.31	7.71	8.49
Panel B: Very close friends									
STEM	-0.096	0.003	-0.196	-0.358	0.081	-0.214	-0.086	0.152	-0.374
	(0.177)	(0.233)	(0.225)	(0.252)	(0.254)	(0.370)	(0.226)	(0.295)	(0.260)
Intercept	3.84	3.85	3.84	4.02	3.61	4.34	3.54	3.47	4.17
Panel C: Good female v. male friends									
STEM	-1.05***	-1.28***	-0.810***	-1.45***	-1.01***	-1.18**	-0.663***	-0.461	-1.45***
	(0.257)	(0.394)	(0.274)	(0.403)	(0.321)	(0.470)	(0.254)	(0.385)	(0.344)
Intercept	0.77	0.77	0.76	0.58	1.03	-0.93	1.67	0.01	1.32
Cutoffs	293	153	140	231	221	206	253	173	120
Students	3,562	1,925	2,062	1,715	1,792	1,251	2,254	2,011	1,683
Student-cutoffs	3,987	1,925	2,062	1,921	1,985	1,396	2,510	2,093	1,894

The table shows heterogeneity for the results in Table 18. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

A9.3 Changes in the 1.5 years after high school

Table A58: Effects on time use on a typical weekday: students from the second follow-up survey

	Doing homework	Playing video games	On social media	Reading	Watching TV	With friends	Working for pay	Caring for others	Doing extra-curriculars
Panel A: End of high school									
STEM	0.128	0.033	-0.512***	-0.110	0.142	-0.065	-0.018	-0.104	0.138
	(0.187)	(0.196)	(0.195)	(0.185)	(0.128)	(0.219)	(0.185)	(0.111)	(0.137)
Intercept	2.44	1.22	3.43	1.28	0.79	2.56	1.52	0.56	0.84
Std. dev.	1.60	1.65	1.70	1.30	1.18	1.77	1.87	1.13	1.35
Panel B: 1.5 years after high school									
STEM	-0.383**	0.072	-0.356**	-0.404*	0.076	0.026	-0.372	0.115	0.154
	(0.185)	(0.125)	(0.170)	(0.225)	(0.087)	(0.163)	(0.285)	(0.125)	(0.111)
Intercept	2.87	0.48	3.01	2.71	0.39	1.91	1.82	0.26	0.54
Std. dev.	1.70	1.08	1.42	1.67	0.76	1.35	2.33	0.97	0.91
Panel C: Change in the 1.5 years after high school									
STEM	-0.511**	0.038	0.156	-0.294	-0.067	0.091	-0.355	0.219	0.016
	(0.231)	(0.198)	(0.194)	(0.255)	(0.151)	(0.241)	(0.313)	(0.159)	(0.162)
Intercept	0.42	-0.74	-0.41	1.44	-0.40	-0.66	0.30	-0.31	-0.30
Std. dev.	2.03	1.56	1.82	1.91	1.27	2.05	2.73	1.46	1.53
Cutoffs	198	198	198	198	198	198	198	198	198
Students	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199	1,199

The table shows is similar to Table 17; however, it is restricted to students from the second follow-up survey and shows effects at different points in time. Variables in Panel A are from the end-of-high-school survey. Variables in Panel B are from the second follow-up survey. Variables in Panel C are the difference between those in Panels B and A. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A59: Effects on friendships: students from the second follow-up survey

	Good friends	**Very close friends**	**Good female v. male friends**
Panel A: End of high school			
STEM	0.592	-0.363	-1.05**
	(0.720)	(0.343)	(0.420)
Intercept	8.43	3.95	0.74
Std. dev.	5.37	2.64	3.87
Panel B: 1.5 years after high school			
STEM	-0.043	-0.014	-0.595
	(0.553)	(0.316)	(0.409)
Intercept	6.56	4.05	0.35
Std. dev.	4.33	2.59	3.15
Panel C: Change in the 1.5 years after high school			
STEM	-0.635	0.349	0.455
	(0.748)	(0.408)	(0.503)
Intercept	-1.86	0.10	-0.38
Std. dev.	5.96	3.42	3.76
Cutoffs	198	198	198
Students	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199

The table shows is similar to Table 18; however, it is restricted to students from the second follow-up survey and shows effects at different points in time. Variables in Panel A are from the end-of-high-school survey. Variables in Panel B are from the second follow-up survey. Variables in Panel C are the difference between those in Panels B and A. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A60: Effects on pyschological outcomes: students from the second follow-up survey

	Wellbeing	**Empathy**	**Grit**	**Trust**
Panel A: End of high school				
STEM	0.051	-0.027	-0.078	0.123
	(0.078)	(0.093)	(0.064)	(0.088)
Intercept	-0.06	0.06	0.05	-0.16
Std. dev.	0.73	0.69	0.61	0.80
Panel B: 1.5 years after high school				
STEM	-0.044	-0.095	0.063	0.129
	(0.088)	(0.090)	(0.076)	(0.104)
Intercept	-0.02	0.16	-0.03	-0.17
Std. dev.	0.73	0.71	0.60	0.86
Panel C: Change in the 1.5 years after high school				
STEM	-0.095	-0.067	0.141*	0.007
	(0.100)	(0.127)	(0.076)	(0.136)
Intercept	0.03	0.10	-0.08	-0.01
Std. dev.	0.89	0.88	0.70	1.06
Cutoffs	198	198	198	198
Students	1,089	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199	1,199

The table shows is similar to Table 14; however, it is restricted to students from the second follow-up survey and shows effects at different points in time. Variables in Panel A are from the end-of-high-school survey. Variables in Panel B are from the second follow-up survey. Variables in Panel C are the difference between those in Panels B and A. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

Table A61: Effects on expectations: students from the second follow-up survey

	Work amount	**Bread-winner**	**Wealth decile**	**Number of children**	**Locale type**	**Traditionalist expectations**
Panel A: End of high school						
STEM	0.005	0.064	-0.260	-0.113	0.139	-0.040
	(0.065)	(0.063)	(0.171)	(0.102)	(0.094)	(0.057)
Intercept	2.79	2.15	7.67	1.88	2.63	0.10
Std. dev.	0.48	0.50	1.40	0.89	0.88	0.50
Panel B: 1.5 years after high school						
STEM	0.036	0.066	-0.283*	-0.037	0.046	-0.052
	(0.042)	(0.067)	(0.145)	(0.090)	(0.094)	(0.063)
Intercept	2.90	2.11	7.59	1.34	2.63	0.11
Std. dev.	0.32	0.48	1.16	0.83	0.82	0.52
Panel C: Change in the 1.5 years after high school						
STEM	0.032	0.002	-0.023	0.075	-0.093	-0.012
	(0.064)	(0.075)	(0.201)	(0.120)	(0.110)	(0.059)
Intercept	0.10	-0.04	-0.08	-0.53	-0.01	0.02
Cutoffs	198	198	198	198	198	198
Students	1,089	1,089	1,089	1,089	1,089	1,089
Student-cutoffs	1,199	1,199	1,199	1,199	1,199	1,199

The table shows is similar to Table 15; however, it is restricted to students from the second follow-up survey and shows effects at different points in time. Variables in Panel A are from the end-of-high-school survey. Variables in Panel B are from the second follow-up survey. Variables in Panel C are the difference between those in Panels B and A. The sample is the same for all outcomes, so it is presented in a single set of rows at the bottom of the table.

A10 The factors that students weigh in their decisions

This appendix digs deeper into the reasons that students report for their choice of college major, and their decision to leave or not attend college. The most important factor that determines choice of major (Table A62) is students' perceptions that it matches their abilities (95 percent), followed closely by matching their interests (94 percent) and leads to job happiness (91 percent). This corroborates the view that the mechanism underlying our results is early exposure to STEM shifting students' self-perceived abilities and interests. It also, of course, increases their earnings prospects which further contributes to a shift toward STEM in college, with earnings prospects identified by 90 percent of students as a factor in college major choice. It is notable that relatively few students report being locked into a college major by their high school major (39 percent), suggesting that they are making an active, rather than default, choice. Friends, who play a significant choice of high school, play only a small role in choice of college major (19 percent).

Table A62: The explanations students selected for why they chose their college major

Explanation	**Share selecting yes**			**Difference: STEM v. Hum./SS**
	All	Assigned to STEM	Assigned to Hum./SS	
The subject matched my abilities	0.95	0.96	0.95	0.01
The subject matched my interests	0.94	0.95	0.94	0.01
The subject would lead to a job that I would be happy with	0.91	0.90	0.92	-0.02
The subject would lead to a job with high earnings	0.90	0.92	0.86	0.06
My parents wanted me to study the subject	0.79	0.79	0.79	0.00
In high school, I learned about career paths related to the subject	0.56	0.57	0.56	0.01
My high school teachers encouraged me to study the subject	0.48	0.52	0.42	0.09
The subject matched what I studied in high school, and it was hard to change	0.41	0.44	0.35	0.10
I thought the subject would be easy	0.25	0.21	0.32	-0.11
The subject is the same as what my friends chose	0.19	0.19	0.20	-0.01

The table shows the share of students who responded yes to the listed possible explanations for why they chose their college major. The data is from the follow-up survey and is not available for students who never attended college. The sample is the 879 students in the RD sample for the follow-up survey who had ever attended college by the time of the follow-up survey.

Students' main reasons for leaving college (Table A63) seem to have to do with loss of interest or the realization that they would not be happy with a career in their program of study (both 58 percent). Much less common are changing their view on career prospects (35 percent), peers (27 percent), and family or financial concerns (4 percent).

Reasons for not joining college after high school (Table A64) are more diffuse, with students citing job opportunities and family obligations (35 percent and 24 percent), alongside the view that their high school curriculum did not prepare them for the program they are interested in (34 percent).

Table A63: The explanations students selected for why they decided to leave college

Explanation	**Share selecting yes**			**Difference: STEM v. Hum./SS**
	All	Assigned to STEM	Assigned to Hum./SS	
I lost interest in the program's subject	0.58	0.53	0.64	-0.10
I realized that the program wouldn't lead to a job that I would be happy with	0.58	0.53	0.64	-0.10
My program was too hard	0.46	0.40	0.55	-0.15
I found a good job opportunity	0.38	0.27	0.55	-0.28
I realized that the program wouldn't lead to a job with high earnings	0.35	0.33	0.36	-0.03
I felt out of place with my peers and the instructors	0.27	0.13	0.45	-0.32
I had family responsibilities that prevented me from completing the program	0.04	0.00	0.09	-0.09
I was unable to pay for the program	0.04	0.00	0.09	-0.09

The table shows the share of students who responded yes to the listed possible explanations for why they chose to stop attending college. The data is from the follow-up survey and is available only for students who left college. The sample is the 26 students in the RD sample for the follow-up survey who had attended and then left college by the time of the follow-up survey.

Table A64: The explanations students selected for why they chose not to attend college

Explanation	**Share selecting yes**			**Difference: STEM v. Hum./SS**
	All	Assigned to STEM	Assigned to Hum./SS	
I found a good job opportunity	0.35	0.36	0.32	0.04
My high school curriculum doesn't prepare me for the programs I'm interested in	0.34	0.33	0.34	-0.01
I have family responsibilities that I need to deal with	0.26	0.28	0.22	0.06
I was not admitted to the programs that I wanted to attend	0.20	0.22	0.16	0.06
I did not pass the baccalaureate exam	0.16	0.15	0.14	0.01
The subject I would study wouldn't lead to a job that I would be happy with	0.16	0.16	0.10	0.06
The subject I would study wouldn't lead to a job with high earnings	0.15	0.13	0.16	-0.03
I am not interested in more school	0.14	0.13	0.16	-0.03
I can't afford college or university	0.13	0.13	0.10	0.03
I would feel out of place with the students and the instructors	0.06	0.05	0.06	-0.01
My high school teachers discouraged me from going to college or university	0.04	0.04	0.02	0.02
I think school is too hard	0.03	0.03	0.02	0.01

The table shows the share of students who responded yes to the listed possible explanations for why they chose not to attend college. The data is from the follow-up survey and is not available for students who ever attended college. The sample is the 167 students in the RD sample for the follow-up survey who had never attended college by the time of the follow-up survey.

Table A65 sheds light on medium-term career expectations. The most important factors that students expect will drive their job choices at age 30 are coworkers and working conditions (99 percent), followed by income (98 percent), and work matching interests and abilities (97 and 96 percent). Location, prestige, and approval of family and friends are in the second tier of expected importance (82, 76, and 73 percent). Fewer students expect lock in based on high school major or teachers to be an important factor in determining their job choices at age 30.

Overall, these results suggest that the interests and abilities that have been shifted by high school exposure to STEM will continue to impact their college and career choices over a longer horizon.

Table A65: The explanations that students expect will drive their job choices at age 30

Explanation	**Share selecting yes**			**Difference: STEM v. Hum./SS**
	All	Assigned to STEM	Assigned to Hum./SS	
The job has good coworkers and working conditions	0.99	0.99	0.99	-0.01
The job provides a high income	0.98	0.98	0.97	0.01
The content of the work involved in the job matches my interests	0.97	0.98	0.96	0.03
The job matches my abilities and educational background	0.96	0.97	0.95	0.01
The job would let me live close to where my friends and family are	0.82	0.81	0.84	-0.03
The job is prestigious	0.76	0.75	0.78	-0.03
My friends and family would approve of me doing the job	0.73	0.75	0.71	0.04
The job is related to what I studied in high school, and it is hard to change	0.48	0.49	0.49	0.00
The job is easy	0.48	0.49	0.48	0.01
My high school teachers encouraged me to do the job	0.47	0.48	0.46	0.02

The table shows the share of students who responded yes to the listed possible explanations after being asked to imagine their job at age 30 and why they chose it. The data is from the second follow-up survey. The sample includes the 1,089 students who form the RD sample for that survey.

A11 Writing out the treatment effect in potential outcomes

A11.1 Basics

For simplicity, consider two treatments: being in a STEM v. HSS track and scoring above v. below a cutoff. The first treatment incorporates the effects of changes in curriculum, teachers, peer gender composition, peer relative ability in math v. language, etc. and is what we're interested in. We consider the second treatment a nuisance term.

Let Y_i be student i's outcome, let $\mathrm{T}_i \in \{\mathrm{S}, \mathrm{H}\}$ be i's track type, and let $\mathrm{A}_i \in \{\mathrm{a}, \mathrm{b}\}$ be whether i scored above or below a cutoff. Write $\mathrm{Y}_i = \mathrm{Y}_i(\mathrm{T}_i, \mathrm{A}_i)$, where $\mathrm{Y}_i()$ is i's potential outcome function. Without loss of generality, write $\mathrm{Y}_i()$ as the sum of four components: $\mathrm{Y}_i(\mathrm{T}, \mathrm{A}) = \alpha_i + h_i(\mathrm{T}) + m_i(\mathrm{A}) + l_i(\mathrm{T}, \mathrm{A})$. Here, α_i is a fixed, i-specific factor that will be eliminated by the quasi-experimental nature of the RD design. $h_i(\mathrm{T})$ is the i-specific main effect of track type, $m_i(\mathrm{A})$ is the i-specific main effect of scoring above v. below a cutoff, and $l_i(\mathrm{T}, \mathrm{A})$ is the i-specific interaction term. The interaction term can be interpreted as the additional effect of scoring above v. below a cutoff when the tracks on either side of the cutoff are of a given combination of types. For a given person, $\mathrm{Y}_i(\mathrm{T}, \mathrm{A})$ can take on four values.

Finally, there are four different types of cutoffs: STEM above, HSS above, STEM (both above and below), and HSS (both above and below). For convenience, call people at these cutoffs Prefer STEM (PS), Prefer HSS (PH), Strongly Prefer STEM (SPS), and Strongly Prefer HSS (SPH), respectively.

A11.2 Treatment effects

The RD design lets us calculate treatment effects for each of the four cutoff types. These treatment effects are always "at the cutoff"—i.e., conditioned on the running variable being equal to 0. However, for simplicity, we omit the conditioning.

For STEM above and HSS above cutoffs, the effects of being on the STEM side of the cutoff are:

- STEM above: $\mathrm{E}[\mathrm{Y}_i(\mathrm{S}, \mathrm{a}) - \mathrm{Y}_i(\mathrm{H}, \mathrm{b})|\mathrm{PS}]$.
- HSS above: $\mathrm{E}[\mathrm{Y}_i(\mathrm{S}, \mathrm{b}) - \mathrm{Y}_i(\mathrm{H}, \mathrm{a})|\mathrm{PH}]$.

For STEM and HSS cutoffs, the effects of being above the cutoff are:

- STEM: $\mathrm{E}[\mathrm{Y}_i(\mathrm{S}, \mathrm{a}) - \mathrm{Y}_i(\mathrm{S}, \mathrm{b})|\mathrm{SPS}]$.
- HSS: $\mathrm{E}[\mathrm{Y}_i(\mathrm{H}, \mathrm{a}) - \mathrm{Y}_i(\mathrm{H}, \mathrm{b})|\mathrm{SPH}]$.

We calculate the average effect of being on the STEM side of the cutoff for STEM above and HSS above cutoffs. This is:

$$\begin{aligned}
&\frac{\mathrm{E}[\mathrm{Y}_i(\mathrm{S}, \mathrm{a}) - \mathrm{Y}_i(\mathrm{H}, \mathrm{b})|\mathrm{PS}] + \mathrm{E}[\mathrm{Y}_i(\mathrm{S}, \mathrm{b}) - \mathrm{Y}_i(\mathrm{H}, \mathrm{a})|\mathrm{PH}]}{2} \\
=&\frac{\mathrm{E}[h_i(\mathrm{S}) - h_i(\mathrm{H})|\mathrm{PS}] + \mathrm{E}[h_i(\mathrm{S}) - h_i(\mathrm{H})|\mathrm{PH}]}{2} \\
+&\frac{\mathrm{E}[\{m_i(\mathrm{a}) + l_i(\mathrm{S}, \mathrm{a})\} - \{m_i(\mathrm{b}) + l_i(\mathrm{H}, \mathrm{b})\}|\mathrm{PS}] - \mathrm{E}[\{m_i(\mathrm{a}) + l_i(\mathrm{H}, \mathrm{a})\} - \{m_i(\mathrm{b}) + l_i(\mathrm{S}, \mathrm{b})\}|\mathrm{PH}]}{2}.
\end{aligned}$$

The first term is what we are interested in and what we call the ATE of STEM v. HSS. It is the effect of being *placed* into a STEM track (rather than getting in due to scoring above or below a

cutoff), averaged over students who prefer STEM and students who prefer HSS The second term is the difference in (a) the effect of scoring above a cutoff and getting into a track of one's preferred type versus scoring below a cutoff and getting into a track of one's next-preferred type for students who prefer STEM and (b) the same effect for students who prefer HSS.

We can't calculate the second term in the previous equation, but we can calculate something similar. Namely, if we compute the difference in the effects of being above the cutoff for STEM and HSS cutoffs, we get:

$$\frac{\mathrm{E}[\mathrm{Y}_i(\mathrm{S},\mathrm{a}) - \mathrm{Y}_i(\mathrm{S},\mathrm{b})|\mathrm{SPS}] + \mathrm{E}[\mathrm{Y}_i(\mathrm{H},\mathrm{a}) - \mathrm{Y}_i(\mathrm{H},\mathrm{b})|\mathrm{SPH}]}{2}$$
$$= \frac{\mathrm{E}[\{m_i(\mathrm{a}) + l_i(\mathrm{S},\mathrm{a})\} - \{m_i(\mathrm{b}) + l_i(\mathrm{S},\mathrm{b})\}|\mathrm{SPS}] - \mathrm{E}[\{m_i(\mathrm{a}) + l_i(\mathrm{H},\mathrm{a})\} - \{m_i(\mathrm{b}) + l_i(\mathrm{H},\mathrm{b})\}|\mathrm{SPH}]}{2}.$$

This is the difference in (a) the effect of scoring above a cutoff and getting into a track of one's preferred type versus scoring below a cutoff and getting into a track of one's next-preferred type for students who strongly prefer STEM and (b) the same effect for students who strongly prefer HSS. Importantly, we find that the quantity is generally 0.[31] As such, we can reasonably assume that the second term in the earlier equation is close to 0 and that what we calculate is the ATE of STEM v. HSS.

31. In fact, the effects of scoring above the cutoff for STEM and HSS cutoffs are both generally 0; thus, their difference is especially close to 0.

A12 The effects of being above a same-curriculum cutoff

In this appendix, we explore whether the outcomes considered in the main paper can be influenced by whether a student scores just above or below a cutoff.

To do this, we adapt our empirical strategy to estimate the effects of being assigned to more or less selective tracks with the same curricula. As in the main paper, we identify up to two cutoffs per student. However, the cutoffs we focus on are different. For students assigned to STEM, we focus on the lowest cutoff such that if a student had scored above that cutoff the student would switch into a more selective STEM track and the highest cutoff such that if the student had scored below that cutoff the student would switch into a less selective STEM track. We define the cutoffs of interest for HSS-assigned students similarly. Also, we use as a running variable students' transition score. (We no longer re-orient the transition score in relation to the STEM side of the cutoff because cutoffs always offer the same curriculum on either side.) We then regress outcomes on indicators for being above a cutoff interacted with cutoff type (STEM or HSS), cutoff fixed effects, and a linear spline in the transition score interacted with cutoff type. Finally, we calculate the simple average of estimated effects of being above a cutoff for STEM and HSS. As in the main paper, we drop students with transition scores equal to the cutoff score or more than 1.25 points away from the cutoff score, and we cluster standard errors by student and cutoff.

Tables A66 and A67 present results for the effects of being above a same-curriculum cutoff for all the outcomes for which we show robustness and heterogeneity when studying the effects of STEM v. HSS curricula. Effects are almost always small and statistically insignificant.[32] This stands in stark contrast with the large effects that we recover from cross-curricula cutoffs.

32. Effects on baccalaureate performance are often significant, but this is mainly a reflection of the large sample size used to estimate them, as they are small in magnitude.

Table A66: The effects of being above a same-curriculum cutoff

Outcome	Coefficient estimate	Standard error	Cutoffs	Students	Student-cutoffs
Panel A: High school enrollment and graduation					
Years of enrollment	0.006*	0.003	1,781	73,627	101,290
Years of STEM enrollment	-0.006	0.008	1,781	73,627	101,290
Graduate	-0.001	0.002	1,781	73,627	101,290
Graduate in STEM	-0.003	0.003	1,781	73,627	101,290
Panel B: Baccalaureate performance					
Take the exam	-0.004***	0.001	2,373	96,902	133,538
Pass the exam	-0.011***	0.002	2,373	96,902	133,538
Exam score	0.011	0.008	2,303	92,484	127,757
Pass in STEM	-0.010***	0.003	1,781	73,627	101,290
Panel C: College outcomes					
College plans at the end of high school: any college	0.010	0.013	382	4,798	6,128
College plans at the end of high school: STEM	-0.008	0.023	382	4,798	6,128
College enrollment one year after high school: any college	0.000	0.017	372	3,944	5,043
College enrollment one year after high school: STEM	0.010	0.020	372	3,944	5,043
Panel D: Academic belief and preference outcomes					
Beliefs about own high school STEM abilities at the end of high school	-0.055	0.050	382	4,798	6,128
Beliefs about own high school STEM abilities one year after high school	0.036	0.091	260	1,153	1,479
Preferences for high school STEM subjects one year after high school	0.075	0.111	260	1,153	1,479
Beliefs about own college STEM abilities one year after high school	0.059	0.094	260	1,153	1,479
Preferences for college STEM subjects one year after high school	0.075	0.112	260	1,153	1,479
Panel E: Career plans one year after high school					
STEM	-0.043	0.042	260	1,153	1,479
Technology or engineering	-0.028	0.035	260	1,153	1,479
Medicine	-0.043	0.032	260	1,153	1,479
Economics and business	0.028	0.045	260	1,153	1,479
Art, education, law, or social services	0.050	0.037	260	1,153	1,479
Other/unsure	-0.007	0.030	260	1,153	1,479
Panel F: Career choices and beliefs 1.5 years after high school					
I would choose to be a tech worker	-0.026	0.040	277	1,406	1,778
Being a tech worker offers good pay	0.006	0.051	277	1,406	1,778
I would enjoy the work content as a tech worker	-0.132	0.125	277	1,406	1,778
Tech offers good coworkers and work conditions	-0.165	0.115	277	1,406	1,778
I am well prepared to be a tech worker	-0.173	0.126	277	1,406	1,778
My friends/family would approve of me being a tech worker	-0.015	0.109	277	1,406	1,778
Panel G: Preferences over ONET job activities 1.5 years after high school					
STEM-related ONET job activities	-0.162	0.232	277	1,406	1,778
Hum./SS-related ONET job activities	0.111	0.129	277	1,406	1,778

The table presents results for the effects of being assigned to a more selective track by scoring above a same-curriculum cutoff. Outcomes are those for which we we show robustness and heterogeneity when studying the effects of STEM v. HSS curricula. See the text of Appendix A12 for details on the regressions that are used to estimate the effects.

Table A67: The effects of being above a same-curriculum cutoff, cont.

Outcome	Coefficient estimate	Standard error	Cutoffs	Students	Student-cutoffs
Panel H: High school satisfaction and curricular fit at the end of high school					
Liked the high school experience	0.038	0.048	382	4,798	6,128
Liked the high school curriculum	0.014	0.048	382	4,798	6,128
Liked the high school peers	0.059	0.058	382	4,798	6,128
Liked the high school teachers	-0.003	0.041	382	4,798	6,128
High school curriculum was a good fit for own abilities	-0.034	0.037	382	4,798	6,128
Panel I: High school satisfaction and curricular fit one year after high school					
Liked the high school experience	-0.070	0.085	260	1,153	1,479
Liked the high school curriculum	-0.070	0.084	260	1,153	1,479
Liked the high school peers	-0.077	0.096	260	1,153	1,479
Liked the high school teachers	-0.118*	0.067	260	1,153	1,479
High school curriculum was a good fit for own abilities	0.067	0.113	260	1,153	1,479
Panel J: Regret over high school application choices one year after high school					
Satisfied with ranking of high school options	0.126	0.092	260	1,153	1,479
If could do over, would make no change	0.014	0.042	260	1,153	1,479
If could do over, would rank STEM tracks higher	0.016	0.024	260	1,153	1,479
If could do over, would rank Hum./SS tracks higher	-0.021	0.028	260	1,153	1,479
If could do over, would rank Technical tracks higher	-0.009	0.010	260	1,153	1,479
Panel K: College satisfaction, curricular fit, and regret one year after high school					
Like the college experience	0.006	0.106	260	1,153	1,479
Like the college curriculum	0.033	0.093	260	1,153	1,479
Like the college peers	0.186*	0.098	260	1,153	1,479
Like the college instructors	0.143	0.088	260	1,153	1,479
College curriculum is a good fit for own abilities	0.100	0.107	260	1,153	1,479
Well prepared for the college curriculum	-0.084	0.130	260	1,153	1,479
Satisfied with ranking of college options	0.215*	0.123	260	1,153	1,479
Panel L: Psychological outcomes at the end of high school					
Wellbeing	0.014	0.033	382	4,798	6,128
Empathy	0.038	0.024	382	4,798	6,128
Grit	0.001	0.026	382	4,798	6,128
Trust	-0.039	0.034	382	4,798	6,128
Panel M: Expectations at the end of high school					
Expected work amount	-0.018	0.019	382	4,798	6,128
Expectations about being the breadwinner	-0.002	0.017	382	4,798	6,128
Expected wealth decile	0.024	0.056	382	4,798	6,128
Expected number of children	0.026	0.037	382	4,798	6,128
Expected locale type	-0.016	0.035	382	4,798	6,128
Traditionalist expectations	0.021	0.023	382	4,798	6,128
Panel N: Political preferences at the end of high school					
Right-wing preferences	-0.027	0.021	382	4,798	6,128
Right-wing economic preferences	0.001	0.025	382	4,798	6,128
Right-wing social preferences	-0.056**	0.028	382	4,798	6,128
Panel O: Time use on a typical weekday at the end of high school					
Doing homework	0.037	0.064	382	4,798	6,128
Playing video games	-0.074	0.074	382	4,798	6,128
On social media	-0.035	0.073	382	4,798	6,128
Reading	-0.014	0.054	382	4,798	6,128
Watching TV	-0.005	0.046	382	4,798	6,128
With friends	-0.047	0.096	382	4,798	6,128
Working for pay	-0.048	0.082	382	4,798	6,128
Caring for others	0.020	0.049	382	4,798	6,128
Doing extracurricular activities	-0.032	0.048	382	4,798	6,128
Panel P: Friendships at the end of high school					
Good friends	-0.039	0.236	382	4,798	6,128
Very close friends	-0.029	0.109	382	4,798	6,128
Good female v. male friends	0.291**	0.146	382	4,798	6,128

The table is a continuation of Table A66.

A13 Cutoff-by-cutoff analysis: regress TEs on first stages on ATS, share female, etc.

TBA