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Sorting, Status, and Shadow Education: How Track Placement Shapes Parental Investment

Sorting, Status, and Shadow Education: How Track Placement Shapes Parental Investment*

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Abstract

Educational tracking—separating students into tracks or schools by ability—is commonplace, but access and preferences for top programs often depend on socioeconomic status (SES), reinforcing inequality. We study shadow education in the context of an early-tracking system, exploiting score cut-offs using a pseudo-regression discontinuity design to isolate the causal effect on parental investments. We find that assignment to the highest track disproportionately increases private tutoring among families in the lowest tercile of SES. This suggests tracking activates a behavioral response among disadvantaged households, which may amplify between-track achievement gaps.

Keywords: education; school choice; tracking; shadow education; private tutoring; student achievement; inequality of opportunity.

JEL Codes: I21, I24, I28, E47, C26

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1 Introduction

School systems worldwide face two major, interrelated challenges. The first is to provide high-quality pedagogically founded instruction tailored to students' needs. The second is to promote social mobility, ensuring equitable access to educational opportunities. Yet, these goals often conflict, and the equity-efficiency trade-off in school tracking represents a fundamental tension in education policy.

A common feature of many global education systems is the grouping of students by ability, either via within-school streaming or between-school tracking. Proponents argue that separating students by ability allows teachers to better tailor instruction to student needs (Duflo et al., 2011), enabling high-achieving students to progress faster and reach higher academic levels. Conversely, critics argue tracking can entrench educational inequalities. Once placed in lower tracks, students often have limited opportunities to move upward, potentially limiting future education and career prospects. Yet early tracking decisions often reflect students' social background as much as their academic potential, with disadvantaged students disproportionately assigned to lower tracks (Reichelt et al., 2019). High levels of socioeconomic segregation between schools can lead to disadvantaged students attending schools with, on average, fewer resources, less experienced teachers, and lower academic expectations, in turn reducing their chances of accession to more academically competitive programs (see, e.g., Dräger et al., 2024). Academic performance at age ten or eleven may therefore not reliably predict future potential, particularly for those from less supportive home environments or non-native language backgrounds (e.g., Buchmann and Park, 2009).

However, while existing research documents the existence of direct effects of tracking on student achievement, the mechanism via which this occurs is less well understood, particularly in a causal setting when abstracting from positive selection effects. In the absence of curriculum differences, potential explanations include teacher quality, differences in school resources, and peer effects in terms of ability or behavior. In our previous work on the Hungarian setting (i.e., Bach et al., 2024), we do not find sufficient evidence that these factors wholly explain the observed positive effects of high-track attendance on student outcomes. One potential explanation that remains underexplored in the literature is that tracking policies indirectly influence student outcomes by altering parental behavior. Parental investment decisions play a crucial role in shaping children's educational outcomes. In this paper, we examine how track assignment at the secondary school level causally affects supplementary educational investments, in particular private tutoring.

Extra-curricular supplementary tutoring is a widespread phenomenon globally, though much of the existing literature is focused on the US and Asia (see, e.g., Zhang, 2018, Matsuoka, 2018, Choi and Park, 2016, Buchmann and Park, 2009) with a comparatively smaller literature focusing on Europe (e.g., Karaçay et al., 2024). Simultaneously, existing research on so-called "shadow education" predominately focuses on the effects of tutoring on achievement (see, e.g., Zhang, 2018) or the characteristics of those who participate in extra-curricular tutoring (i.e., Karaçay et al., 2024, Baker et al., 2001). The mechanisms via which institutional factors influence family-level decision-making regarding these investments remain less understood, with comparatively few studies investigating differences in the context of tracking (see, e.g., Stasny, 2021 for the Czech Republic; Entrich and Lauterbach, 2023 and Guill and Lintorf, 2019 for Germany; and Benz, 2024 for Switzerland).

Existing research demonstrates that socioeconomic background shapes parental beliefs and attitudes toward tracking in hierarchically ordered school systems. High-SES families typically view tracking decisions as mechanisms to preserve or replicate their socioeconomic position, leading parents to advocate for high-track placement even when teacher recommendations suggest otherwise (Grewenig, 2022; Osikominu et al., 2021). For low-SES families, however, preferences for certain academic tracks or programs may more frequently reflect strategic investments in children's future economic mobility. These beliefs are relatedly important in the literature on the intergenerational persistence of earnings, in which parental investments play a critical role in amplifying or mitigating socioeconomic gaps. For instance, evidence suggests increased parental investment by low-SES families can narrow achievement gaps, while high-SES families' ability to optimize investments sustains inequality (Kang, 2024; Beam et al., 2022; Wolf and McCoy, 2017).

The literature on tracking primarily relies on two approaches: cross-institutional variation—often from de-tracking reforms or regional and cross-country differences (see, e.g., Hanushek and Wössmann, 2006)—and regression discontinuity designs exploiting admission thresholds (see, e.g., Dustmann et al., 2017). While the former may conflate tracking effects with concurrent institutional changes, the latter typically identifies local effects at the margin. Our study similarly employs an RDD framework but exploits rich variation in admission cutoffs across decentralized Hungarian programs to estimate effects at different margins across the achievement distribution. Leveraging a pseudo-RDD based on score cut-offs in the track assignment process, we demonstrate how assignment to a higher academic track leads to systematic differences in parents' willingness to invest in supplementary tutoring. Our identification strategy exploits quasi-random variation in track assignment near these cut-offs, allowing us to isolate the causal effect of track placement on parental investment decisions. This approach addresses potential endogeneity concerns that have historically complicated research on the relationship between institutional structures and family-level educational choices. Specifically, better students differentially enroll in the highest track due to a combination of endogenous preferences for high-track programs and selection on the part of schools.

We find causal evidence that for students from more deprived socioeconomic backgrounds, assignment to the highest academic track leads parents to allocate more resources to students, i.e., through increased investment in private tutoring. This finding is consistent with existing evidence that low-SES parents often reallocate resources when given access to higher-quality education, as they perceive greater returns to these investments in improving their child's future outcomes (see, e.g., Kang, 2024 and Beam et al., 2022), and may even view high-track accession as an opportunity to "catch up" (Attanasio et al., 2020; Müller, 2021). In contrast, we also observe a reduction in mathematics tutoring among high-SES students, which may reflect beliefs about diminished marginal returns to additional tutoring for families already benefiting from high-quality education or elite peer effects (Cattan et al., 2022; Attanasio et al., 2020).

That socioeconomic differences manifest in how parents respond to tracking opportunities, independent of student ability, indicates socioeconomic differences in beliefs not only influence initial track placement but may also shape subsequent investment decisions. In addition to providing evidence for the role of institutional signals in shaping parental investment strategies, our results suggest track placement serves as an important mechanism through which educational systems can inadvertently amplify existing socioeconomic disparities. Our findings therefore also contribute to discussions on how inequalities may perpetuate across generations, as well as a growing literature on the interaction between institutional structures and family-level educational decisions, offering important insights for policymakers considering the broader implications of tracking policies in education systems.

This paper proceeds as follows. Section 2 describes the data and provides a descriptive overview. Section 3 introduces our empirical approach. Section 4 presents our results and Section 5 concludes.

2 Data

To investigate how parental investments are linked to educational stratification, we focus on the transition between primary and secondary school that takes place after the 8th grade. Figure A.1 illustrates the structure of the Hungarian education system and details potential progression pathways between the different academic levels. For most students, tracking begins with assignment to one of three secondary school types: vocational training schools (lowest track), vocational secondary schools (intermediate track), and grammar schools (highest track). These assignments are largely determined by participation in a centralized matching procedure conducted when the students are in the 8th grade.[1]

Both intermediate and high track programs follow a common general education curriculum for the first two years post-track assignment, though the optional courses taken from 11th grade onward in the intermediate track may be more vocationally oriented, and students from both tracks can take the maturity examination at the end of the 12th grade. Those attending the lowest track alternatively specialize in a vocational training pathway terminating in a lower-level vocational qualification and are therefore unable to take the maturity exam that allows access to higher education. See Bach et al. (2024) for further details.

Based on their future goals and academic interests during the 8th grade, students submit a rank-order preference list of programs, consisting of specific school-course combinations. These preference lists are not limited in terms of length or geographically (e.g., there are no districting restrictions), though they must be strictly ordered. On the school side, all students who list a particular program must in turn be strictly ranked so long as the school deems them "acceptable" for admission. Programs are able to set their own criteria determining how applicants are prioritized, including 8th-grade centralized examination scores, school grades, and, in some cases, oral interviews, as well as student-specific characteristics, e.g., religious affiliation. The student-proposing deferred acceptance (DA) algorithm (Biró, 2008) is then used to perform a computerized matching process: taking into account students' priority at individual programs, program capacities, and students'

[1]A small number of high track programs with an extended duration recruit students in the 4th and 6th grade (affecting approximately 5.3% of students). These programs are excluded from our analysis because they do not participate in the centralized matching procedure in the same year. Given that our identification strategy relies on students who are *at risk* of assignment to the highest track, and are near the 8th grade admission cutoffs of individual programs, these "always seated" students should not affect our results.

preferences over schools.[2]

Our analysis, therefore, relies on two key sources of data: administrative data from the matching procedure—e.g., students' preference lists and programs' rankings over students, and individual student survey data.

KIFIR.[3] Our source of administrative data is KIFIR, which, in addition to the outcomes of the 2015 centralized matching procedure for Hungarian 8th grade students, contains information about students' preferences, programs' rankings of students, and administrative information about individual programs. For 2015, KIFIR contains information for 88,401 students who applied to 6,181 programs (i.e., school-course combinations) across 1,035 school sites. On average, students applied to 4.5 schools, and 94.4% of students were matched via the mechanism.

National Assessment of Basic Competencies (NABC). Our source of student-specific data, containing information about national test scores, school grades, and individual and family background characteristics, comes from the 2013, 2015, and 2017 waves of the NABC. Tests administered via the NABC are curriculum-independent and designed to measure fundamental competencies in reading and mathematical literacy.[4] In addition to test scores, the NABC records responses to voluntary student surveys (with a response rate of approximately 80%) and includes not only sociodemographic background characteristics, academic history, and future aspirations, but also extra-curricular activities—to include participation in extra-curricular tutoring relating to school subjects, music, and sports.

After linking KIFIR administrative data to the NABC survey data via individual student identifiers, we have information on student characteristics pre- and post-tracking for 54,013 students matched to secondary schools via the 2015 centralized matching procedure.[5]

[2]See Appendix C for a step-by-step explanation of the DA algorithm.

[3]KIFIR is an acronym for *"középfokú felvételi információs rendszer"*, which can be translated as "secondary enrollment information system".

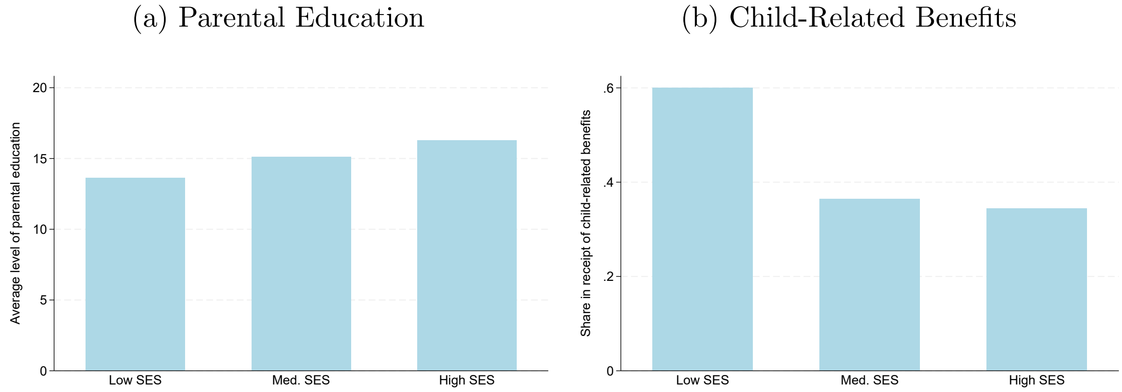
[4]Tasks are designed to test students' abilities to problem solve, i.e., retrieving information from texts or computing a balance sheet, and are similar to the core components of the PISA test.

[5]In Table B.1 we demonstrate missing values in the 2017 follow-up wave of the NABC (e.g., 10th grade) are not a function of previous performance, student characteristics, or the probability of assignment to the highest track. We are therefore unconcerned about selective attrition.

2.1 Socioeconomic Status and Student Performance

A student's socio-economic family environment (SES) is measured using a one-dimensional index of relative deprivation (the so-called CSH Index), constructed by the Hungarian Office of Education based on a range of indicators relating to the student, their parents, and the family environment. As in Bach et al. (2024), for the heterogeneity analysis by SES we divide the distribution of the CSH Index into three equally sized groups (terciles). Figure 1 illustrates the relationship between this measure and other factors relevant to schooling, including the average level of parental education (panel a) and the share of families in receipt of child-related benefits (panel b) for the 2013 wave of the NABC (i.e., pre-tracking).

Figure 1: CSH and Education-Related Dimensions of SES



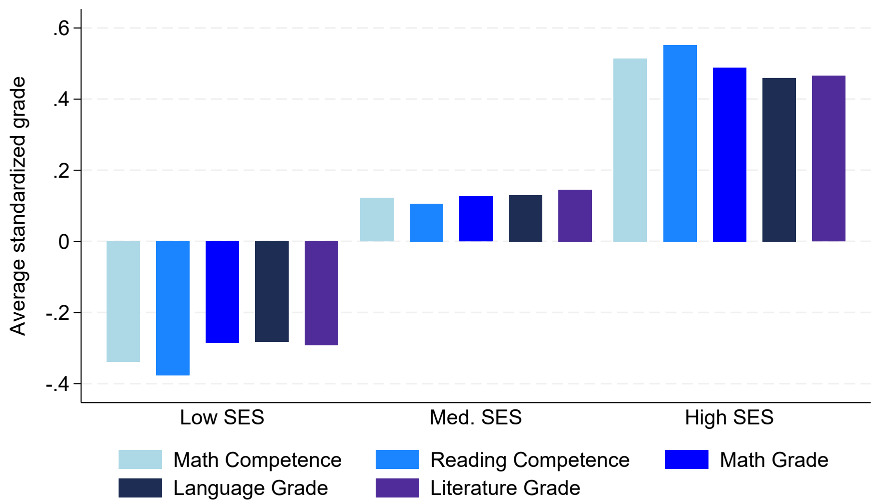
Notes: Parental education varies on a scale from 11 (did not finish primary school) to 17 (master's degree).

The average level of parental education, in terms of the years of schooling, for students in the lowest tercile of SES is 13.64 (secondary vocational qualification), and for students in the highest tercile is 16.28 (university degree). Child-related benefits, including discounted dining or free school lunch, free textbooks, or regular child protection support from the government, are particularly concentrated in the lowest tercile of our SES measure.

In Bach et al. (2024) we investigate the causal effects of admission to the highest track on university aspirations and academic achievement two years post-assignment. We find that admission to a high-track program improves standardized test scores by 0.11 standard deviations, with particularly strong effects for mathematics (0.14 SD). These learning gains vary only slightly by SES and baseline achievement, suggesting those from low SES backgrounds benefit at least as much from high-track admission. Nevertheless, students from relatively worse-off backgrounds are both less likely to apply and to be accepted into the higher track. These results are consistent with existing evidence which suggests accession differences by SES may in part be due to differences in academic performance arising from factors outside of the student's control (see, e.g., Dräger et al., 2024), and the finding that those from more deprived backgrounds are likely to have lower educational aspirations, independent of ability (Zimmermann, 2020).

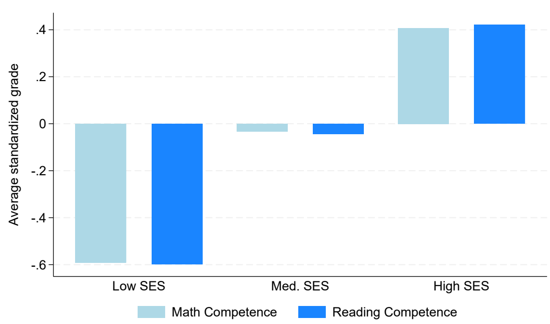
Figure 2: Differences in Academic Achievement by SES

(a) Pre-Tracking Academic Achievement by SES

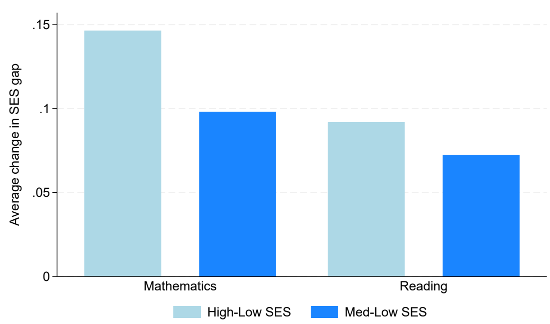


(b) Post-Tracking Academic Achievement by SES

i. Post-Tracking Test Scores



ii. Growth in Achievement Gap



Notes: Panel (a) depicts pre-tracking grades and test scores. In Panel (b), i. reports post-tracking 10th-grade test scores by SES, while ii. depicts the differences in changes in average standardized test scores between 8th and 10th grade. Both 8th and 10th-grade test scores and grades are standardized at the national level.

In our setting, Panel (a) of Figure 2 shows that substantial differences in average test scores and teacher assessments by SES are already evident in the 8th grade, indicating inequalities in learning outcomes conditional on a student's family environment exist even before track assignment. Based on our previous findings, access to the highest track could contribute to a reduction in inequality in academic achievement and higher education aspirations. However, given differential rates of accession to the highest track by SES, tracking may instead amplify these gaps, and potential learning gains are typically not realized for students from relatively more deprived backgrounds. As a consequence, Panel (b) of Figure 2 demonstrates that not only are there substantial differences in average standardized test scores two years post-tracking, but the *gap* in achievement by SES increases pre- and post-tracking.

However, while the growth in educational inequality between the lowest and highest terciles of SES—particularly in regard to mathematics—can in part be ascribed to differences in track accession by socioeconomic background, the precise mechanism via which participation in the highest track positively affects student performance is not well understood. Particularly given the context of the Hungarian setting, wherein both the intermediate and high-track programs follow a common general education curriculum for the 9th and 10th grades. In the following, we therefore explore one plausible mechanism; that is, assignment to the higher track affects family decision-making regarding compensatory investments in children's human capital outside of the classroom.

2.2 Who Participates in Shadow Education?

Table B.3 provides descriptive statistics for those participating in extra-curricular tutoring pre-track assignment. There are no large gender differences evident, though students participating in more than one type of tutoring are slightly more likely to be female. There are also no large differences in age, suggesting participation in tutoring is not driven by those repeating a grade and requiring remedial assistance. The rate at which students participate in tutoring increases with SES, as proxied by the CSH Index, and more intensively tutored students are also less likely to be from a deprived neigborhood, and more likely to have at least one parent that completed the maturity exam or attended higher education. On average, tutored students also have much higher test scores in both mathematics and reading.

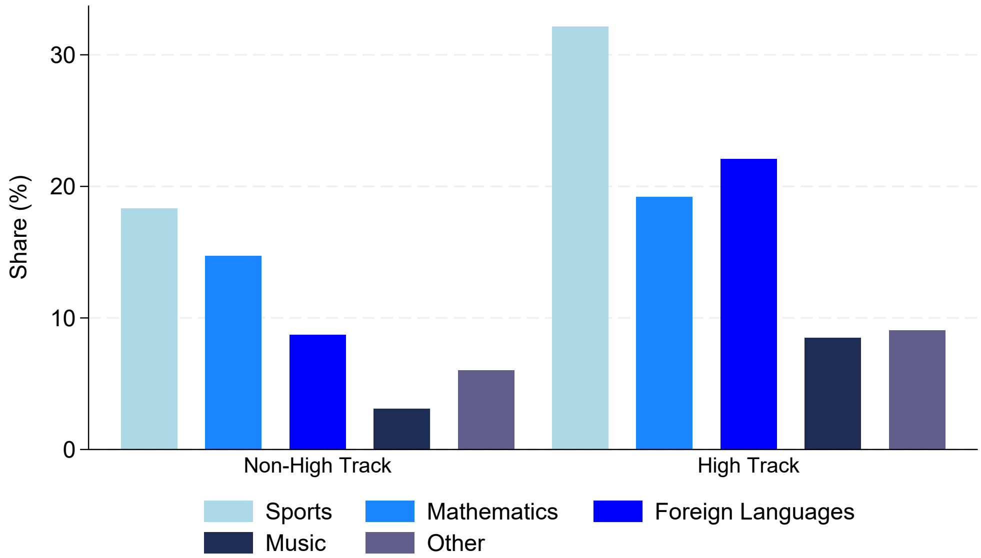
This is important, as high-achieving students are simultaneously more likely to be admitted to a high-track program but are also more likely to participate in tutoring. This is reflected in Table B.4, which provides descriptive statistics post-track assignment by academic track. Not only are there notable track differences in SES, parental education, and gender, with females attending high-track programs at a higher rate than males, but those attending a high-track program have much higher average test scores both pre- and post-tracking. This suggests naïve estimates of the effect of attending a high-track program on tutoring participation are likely affected by positive selection on student ability. In Section 3, we describe our empirical strategy and outline the steps we take to overcome this limitation.

Before examining the causal effect of academic track type on participation in tutoring, however, we first examine descriptive statistics of between-track differences in predictors of tutoring participation. Table B.5 presents the results of a logistic regression model, wherein indicators for 10th-grade participation in at least one type of tutoring and mathematics tutoring, respectively, are regressed on individual student characteristics, standardized 8th-grade test scores, and pre-tracking aspirations toward higher education. The results demonstrate notable differences in terms of both magnitude and significance. For example, higher baseline standardized mathematics test scores are associated with a reduced likelihood of participating in tutoring for lower-track students, but the coefficient is much smaller and not statistically significant for high-track students.

Similarly, the receipt of social benefits is in general associated with a reduced likelihood of participating in at least one type of tutoring and is highly statistically significant across models, but the negative coefficient is twice as large for those not admitted to the higher track. University aspirations are also highly statistically significant in all cases and are positively associated with participation in tutoring, but the coefficients are much larger for those enrolled in the lower tracks. Furthermore, there are notable gender differences. Females are, in general, much more likely to participate in tutoring than males. But while the coefficients are highly statistically significant across all specifications, the magnitudes are noticeably different between tracks conditional on tutoring type. For mathematics tutoring, the coefficient is more than twice the size for individuals in the lower tracks. However, females in the highest track are much more likely to participate in at least one type of tutoring in general.

The type of tutoring students participate in therefore differs between tracks. Figure 3 further illustrates the relative proportions of students participating in extra-curricular tutoring by subject and shows that although high-track students are more likely to participate in tutoring in general, those in lower-track programs are more likely to participate in extra-curricular sports coaching or mathematics tutoring, while those in the highest track are more likely to attend foreign language tutoring than mathematics tutoring.

Figure 3: Differences in Extra-Curricular Tutoring by Track



Notes: Figure 3 depicts 10th-grade participation in extra-curricular tutoring by subject and whether or not the student is enrolled in a high-track program.

3 Empirical Strategy and Identification

Recovering the causal effect of secondary school track assignment on parental decisions regarding supplementary educational investments is empirically challenging. First, potential endogeneity issues arise if school track assignment is influenced by factors correlated with tutoring participation, such as student ability or parental preferences. For example, high-achieving students (and their parents) may be more likely to apply to high-track programs, and simultaneously more inclined to invest in tutoring, creating a spurious relationship between track assignment and tutoring participation. Second, selection bias is of concern when better students are more likely to be admitted to better schools.

Hungary uses the Deferred Acceptance (DA) algorithm to match students with schools (see Appendix C for a description of the procedure). In a system where program admissions are determined by a centralized assignment mechanism, program offers are a function of student preferences, schools' rankings of students, and program capacity constraints. The strict student rankings used as the basis of the matching procedure are based on e.g., prior academic performance, entrance examinations, etc., which are themselves influenced by preexisting disparities in resources and opportunities. To recover the causal effect of admission to the highest track on participation in tutoring, we follow a similar procedure to our previous work in Bach et al. (2024), wherein we leverage randomness embedded in the centralized assignment mechanism used for secondary admissions in Hungary, based on methodological advances by Abdulkadıroğlu et al. (2022). Our identification strategy is based on the principle that for students empirically *near* the admissions thresholds of individual ranked programs, track assignment is limited by individual program capacities – not endogenous differences in student characteristics. That is, we exploit exogenous variation in track assignment through a natural pseudo-regression discontinuity design (RDD) for students at the margin of admission to the highest track.

Implementing this requires a two-step procedure. First, we construct a scalar function of student preferences over individual programs, or the *local DA propensity score*. This describes the relative "risk" that a student is assigned to the highest track based on a) their own preferences over programs, and b) their likelihood of admission (or "local risk") at each individual program to which they have applied given individual program capacity and the program's ranking of the student. This summative measure takes into account both student and school priorities while abstracting from the full preference profile, which may span a number of preference "types" approaching the sample size. Saturated regression conditioning on the local propensity score eliminates always-assigned and never-assigned students with a score of 0 or 1, respectively. The identifying variation comes from the remaining students with a non-degenerate probability of assignment to a high-track program.

The second step involves defining a narrow window around individual programs' admissions thresholds, or cut-offs, excluding programs with fewer than 2 observations on either side of the cutoff. In this setting, the cut-offs are determined by individual program capacities and thus the rank of the last admitted student. Note that for the main analysis, bandwidths are not computed locally for individual programs. Rather, we use a common bandwidth of 0.25 (as in Bach et al., 2024). This bandwidth was chosen based on several related criteria: it is the threshold bandwidth beyond which estimates are stable and for which a placebo test on 8th-grade outcomes indicates a null effect (see Figure A.2). In an additional robustness test, we construct the selected sample based on computing locally optimal bandwidths. To do this, we follow the extensions to Imbens and Kalyanaraman (2012) proposed in Calonico et al. (2017) and Calonico et al. (2019), and determine the mean square error (MSE) optimal bandwidth choice for individual programs.

There is a large degree of variation in academic ability across high-track programs as shown in Figure A.3, which depicts the distribution of baseline standardized test scores for the lowest-scoring student admitted to each high-track program relative to the overall population for (a) mathematics and (b) reading, respectively. Given there is not a universally applicable high-track admissions threshold, the approach described above has the added benefit of a large degree of variation in prior achievement for students in the selected sample. Per Figure A.4, while Panel (a) shows high-track students generally have higher 8th-grade average test scores, Panel (b) demonstrates there is substantial common support between our sample of students who are "at-risk" of admission to the highest track and the universe of Hungarian students. We are therefore able to estimate the local average treatment effect of admission to the highest track on participation in extra-curricular tutoring for students at different points on the prior achievement distribution.

For a more detailed theoretical overview, see Abdulkadiroğlu et al. (2017) and Abdulkadıroğlu et al. (2022). For a more limited description of how this achieves identification in the Hungarian setting, see Bach et al. (2024).

3.1 Validation of Empirical Design

Our empirical strategy approximates randomized assignment to high-track programs by limiting the sample to students who are "at-risk" of high-track assignment. In Table B.6 we demonstrate that offers for high-track programs in the 2015 round of the centralized assignment procedure are as good as random after controlling for the local propensity score and running variables. For the full sample of students, Column (1) shows large, statistically significant differences in pre-tracking student characteristics for those offered a place in a high-track program. There is evidence of positive selection in, e.g., baseline 8th-grade achievement, tutoring participation in the 6th and 8th grades, gender, SES, etc., consistent with the sample statistics reported in Table B.4. In Column (2), however, where we restrict the sample to those "at-risk" students and include saturated propensity score and running variable controls, we show that these differences are both much smaller in magnitude and not statistically significant. Conditioning on the local propensity score for high-track assignment therefore reduces the risk of selection effects and omitted variable bias on the results reported in the next section.

4 Results

In the following, the fully saturated specifications include controls for the propensity score, running variables (i.e., distance from the cutoff at individual programs), baseline test scores in the 8th grade, and baseline participation in tutoring in the 6th and 8th grades. We control for individual student background characteristics, including age, gender, SES, whether the student is from a deprived neighborhood, whether their parent is a single mother, receipt of child-related benefits, whether the student has previously repeated a grade, their parents' highest level of academic attainment, and subjective family financial strain. Finally, we control for potential family-led support in the pre-tracking period, including the presence of siblings in the household, and the frequency with which parents a) assist with homework, b) discuss things the student has learned at school, c) discuss things the student has read, or d) attend parent-teacher conferences. See Table B.2 for further details.

As described previously, we instrument enrollment in the highest track with an offer of a high track place. Table B.7 presents the first-stage results of this procedure. In the fully saturated model, enrollment in the matched high-track program is probabilistic. There are two important reasons for this. First, not all students accept the place to which they are matched, e.g., due to a change in circumstances, a family move, or even a change in preferences for another subject specialty (given offers are for specific school-course combinations). Second, some students who are not matched in the first round ultimately enroll in a high-track program in subsequent admission rounds organized at the school level. Column (5) therefore indicates that receipt of an offer for a high-track place increases the likelihood that a student ultimately enrolls in a high-track program by approximately 66 percentage points.

Table 1 reports the main results for the pseudo-RDD procedure, and demonstrates a substantial, positive effect of high-track enrollment on participation in tutoring for low SES students. The results are both large in magnitude and statistically significant. For mathematics tutoring, the effect size is smaller though still both positive and statistically significant.

Table 1: Average Effects of High Track Enrollment on 10th Grade Participation in Extra-Curricular Tutoring

	(1)	(2)	(3)	(4)	(5)
Panel A: Dep. Var.: Participation in Tutoring					
High Track	0.120	0.076	0.077	0.114	0.108
	(0.098)	(0.097)	(0.097)	(0.090)	(0.090)
High Track × Low SES	0.304***	0.283**	0.289**	0.310***	0.311***
	(0.114)	(0.112)	(0.113)	(0.105)	(0.106)
High Track × Med. SES	0.056	0.005	0.011	0.069	0.056
	(0.127)	(0.126)	(0.126)	(0.120)	(0.119)
High Track × High SES	-0.043	-0.100	-0.109	-0.079	-0.086
	(0.141)	(0.140)	(0.140)	(0.127)	(0.127)
Panel B: Dep. Var.: Participation in Mathematics Tutoring					
High Track	0.000	-0.014	-0.013	0.012	0.010
	(0.041)	(0.042)	(0.042)	(0.041)	(0.041)
High Track × Low SES	0.063	0.049	0.056	0.083*	0.084*
	(0.048)	(0.049)	(0.049)	(0.047)	(0.047)
High Track × Med. SES	0.030	0.012	0.015	0.039	0.034
	(0.057)	(0.057)	(0.057)	(0.056)	(0.055)
High Track × High SES	-0.111*	-0.126**	-0.136**	-0.112**	-0.116**
	(0.060)	(0.061)	(0.061)	(0.057)	(0.057)
N	2,518	2,518	2,518	2,518	2,518
Propensity score FE	✓	✓	✓	✓	✓
RDD controls	✓	✓	✓	✓	✓
Student controls		✓	✓	✓	✓
Baseline test scores			✓	✓	✓
Baseline tutoring				✓	✓
Family-led support					✓

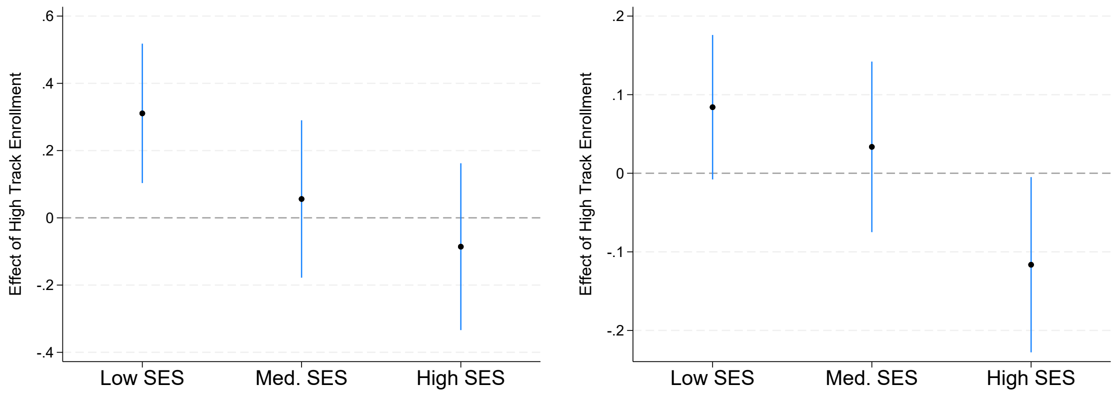
Notes: In addition to saturated propensity score and running variable controls, we iteratively control for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2). The sample is limited to applicants with non-missing baseline test scores. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For high SES students, on the other hand, enrollment in a high-track program for a marginal student actually decreases the likelihood of participation in extra-curricular tutoring, and for mathematics tutoring in particular this effect is both negative and statistically significant. These results are reflected in Figure 4 for (a) tutoring in general and (b) mathematics tutoring, respectively.

Figure 4: Heterogeneous Effects on Tutoring Participation by SES

(a) All Tutoring

(b) Mathematics Tutoring



Notes: Panel (a) reports the average effect of high-track enrollment on 10th-grade participation in tutoring by tercile of SES. Panel (b) reports the effect on mathematics tutoring, in particular. In addition to saturated propensity score and running variable controls, coefficients were estimated controlling for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2 for further details).

The effect of high-track enrollment declines with SES, illustrating a change in extra-curricular tutoring participation at the margin of admission to the highest track. We do not find *significant* differences by gender (see Figure A.5), or prior achievement in reading and mathematics (see Figures A.6 and A.7, respectively), suggesting that these mechanisms are not driving the main results.

A related concern is that tutoring may be a necessity for low-SES students in particular to keep up when assigned to high-track programs. In a further decomposition of heterogeneity in prior achievement for those from low and high SES backgrounds, we find no evidence of this (see Figure A.8). In Panel (a), when dividing the SES distribution into above and below-median groupings, for below-median SES students we find positive effects of high-track enrollment on tutoring for both above and below-median ability. Similarly, in Panel (b), when limiting the prior achievement distribution only to those in the 2nd to 8th deciles of ability measured in terms of 8th-grade standardized test scores, we find similar effects to the main results.

We are also able to characterize the extent to which the effects on tutoring are driven by the effects on mathematics tutoring. Table B.8 reports the effects for all tutoring excluding mathematics (Panel A) and non-academic tutoring (Panel B), respectively. For high SES families, any negative effects of high-track assignment on tutoring participation are driven by the specific effect on mathematics tutoring and are otherwise close to zero. For low SES families, however, this is not the case. There are positive effects of high-track assignment on both mathematics tutoring and tutoring more generally, even after abstracting from the mathematics effect. Further, we are able to show that the substitution of investments from non-academic to academic extra-curricular tutoring is not driving the main results; given investment in sports and music coaching also increases (see Panel B of Table B.8).

Finally, in a robustness test for which the selected sample is alternatively constructed based on computing the locally optimal bandwidths for individual programs, the direction, size, and magnitude of the effects of high-track assignment on tutoring participation are largely similar to the main results (see Tables B.10 and B.11). However, the estimated coefficients lose some significance in the SES disaggregations. This occurs for two reasons: First, the selected sample is approximately 10% smaller due to the on-average smaller bandwidths, especially for larger programs (leading to reduced power for the heterogeneity analyses). Second, and following from the first, the balancing is poorer (see Table B.9). For this reason, we prefer the specifications computed using a global bandwidth, but it is nevertheless a reassuring exercise given the similarity of the estimated coefficients.

5 Discussion

In Hungary, the use of tracking at the secondary level appears to shape the shadow education landscape. In the two years post-assignment, students in the highest track are much more likely to participate in tutoring in general and are more than twice as likely to be tutored in more than one subject (see Table B.4) than the intermediate and lower tracks. Naive estimation also reveals notable differences in the predictors of extra-curricular tutoring participation between tracks (see Table B.5). To understand whether compositional differences in student populations are driving these findings, we explore how track assignment causally affects parental decisions regarding supplementary educational investments, like tutoring.

We find that for students at the margin of admission, admittance to the highest track disproportionately increases parental investment in tutoring for families in the lowest tercile of SES for tutoring in general, as well as specific effects on mathematics tutoring and non-academic tutoring. On the other hand, high-SES students are less likely to participate in extra-curricular mathematics tutoring than their high-SES counterparts who are not matched to a high-track program. This suggests that school tracking not only affects students' academic opportunities but also activates a behavioral response in parents, particularly those from disadvantaged backgrounds. Moreover, it indicates a caveat to Betts (2011)'s assumption that academic tracking acts as a substitute for private tutoring, and that admittance to the highest track may reduce demand for tutoring.

Our findings instead suggest that while this may be true for high-SES students at the margin of admission, it is not true for lower-SES families (and recall, we find no substantial differences by baseline academic achievement). Conversely, for low-SES families, gaining access to a higher-track school or program may serve as a signal that their child has potential for upward mobility, motivating parents to reallocate limited resources toward tutoring. These investments may reflect both parental aspirations and the recognition of heightened academic demands or expectations associated with high-track programs. However, for those not admitted to the highest track, there may be a disincentive to invest in tutoring if parents perceive reduced returns. If placement in a lower-track school is interpreted as a cap on future opportunities, families might deprioritize additional academic support; creating a self-reinforcing cycle of lower expectations and diminished outcomes.

The dynamic interplay between institutional factors, like tracking policies, and family-level decision-making regarding human capital investments could further entrench existing inequalities, as students in lower-track schools may receive less external support, exacerbating between-track achievement gaps. This is consistent with the findings of Stasny (2021), which suggest that between-track achievement heterogeneity in the Czech setting may be derived in part from the differentiated use of shadow education between students of academic and regular tracks. Our results therefore have important implications for educational equality and underscore the importance of ensuring school tracking policies are accompanied by interventions that provide adequate academic support systems accessible to families, regardless of a child's track placement or a family's ability to pay.

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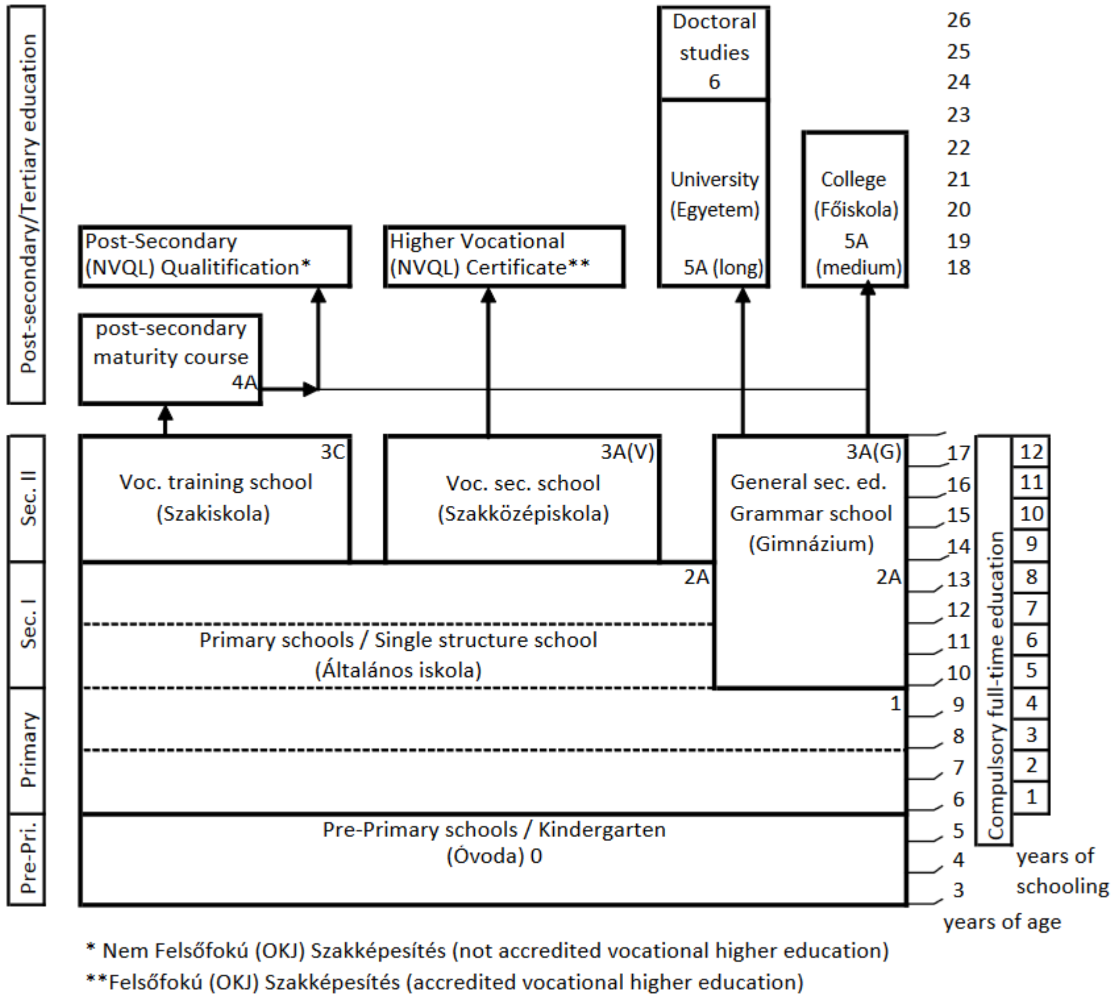
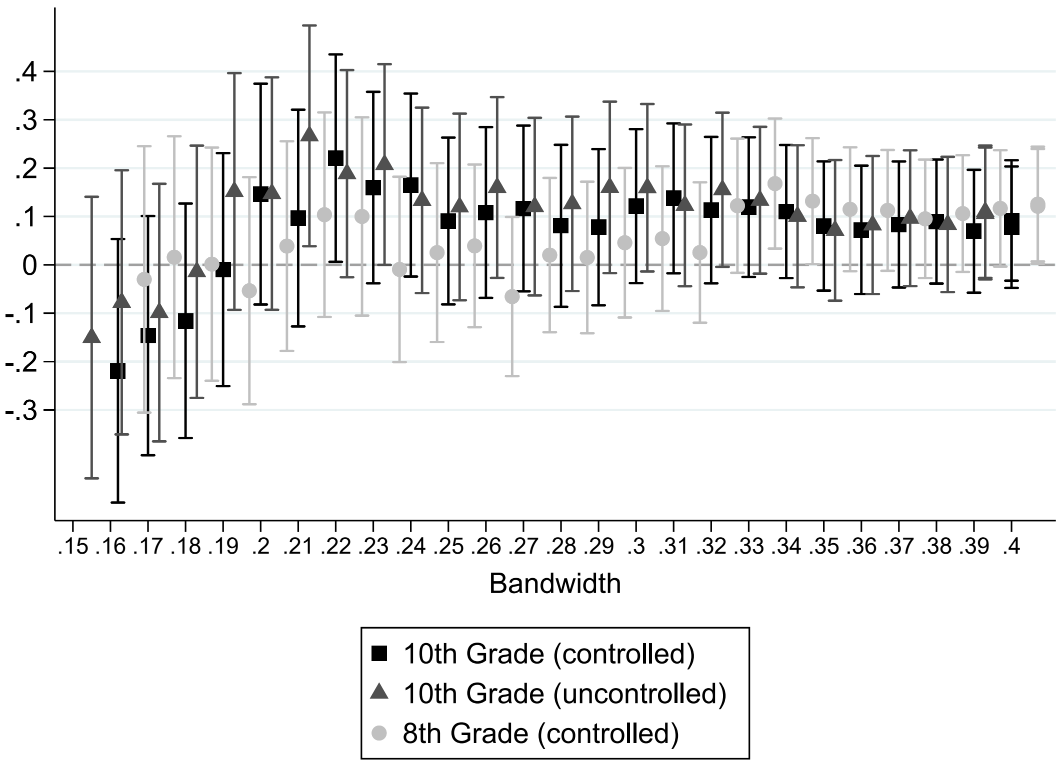
A Additional Figures

Figure A.1: The Structure of the Hungarian Education System



Notes: The figure illustrates the structure and progression of the Hungarian educational system pre-primary to tertiary education. *Source:* Bukodi et al. (2008).

Figure A.2: Bandwidth Sensitivity Analysis for All Tutoring

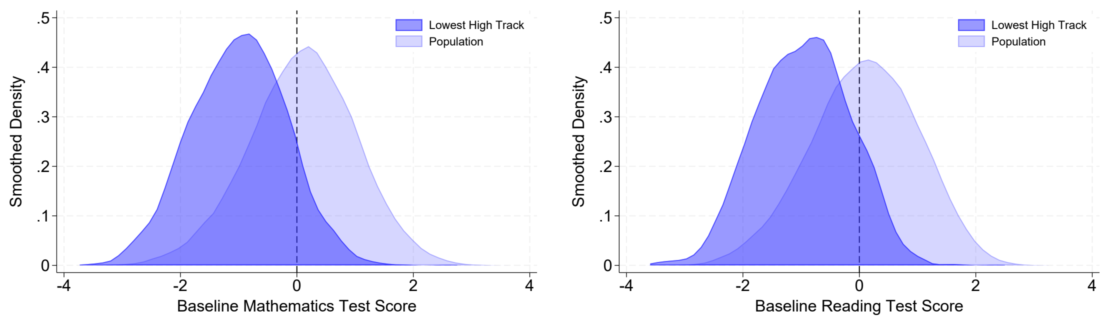


Notes: Figure A.2 demonstrates the sensitivity of the estimation procedure used to compute the main results to the choice of bandwidth. It depicts the estimated coefficient and associated standard errors for the fully saturated model using a) 10th-grade outcomes and the controls described in Table B.2, b) 10th-grade outcomes in an uncontrolled setting, and c) a placebo test using 8th-grade outcomes.

Figure A.3: Distribution of 8th-Grade Standardized Test Scores for the Lowest Scoring Students Admitted to High-Track Programs

Panel (a): Mathematics

Panel (b): Reading

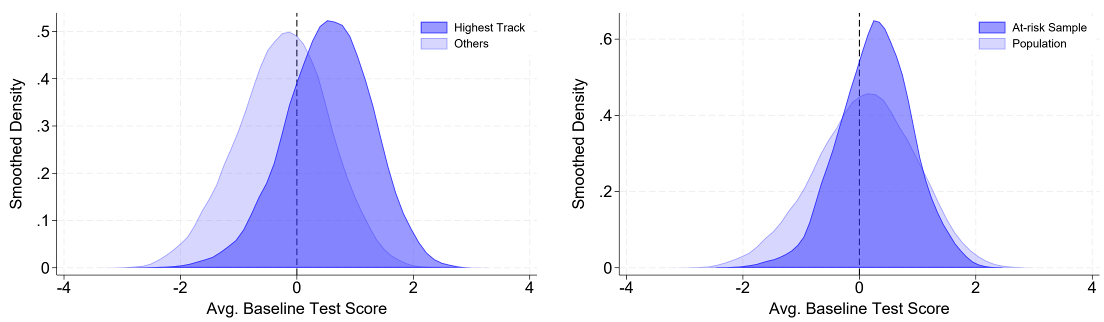


Notes: Figure A.3 plots kernel density estimates of the minimum baseline standardized test scores needed to be admitted to individual high-track programs relative to the overall student population. That is, using baseline test scores measured in the 8th-grade pre-track assignment for (a) mathematics and (b) reading, respectively, we plot the standardized test score of the lowest-scoring student admitted to each high-track program.

Figure A.4: Distribution of 8th-Grade Average Standardized Test Scores

Panel (a): Track Type

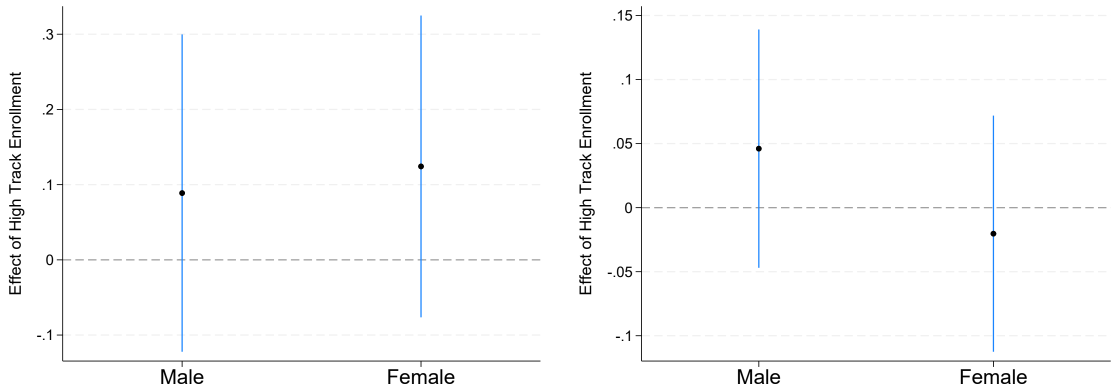
Panel (b): Full and At-Risk Samples



Notes: Figure A.4 plots kernel density estimates of average baseline standardized test scores measured in the 8th-grade pre-track assignment by (a) track type, and (b) for the full and at-risk samples.

Figure A.5: Heterogeneous Effects on Tutoring Participation by Gender

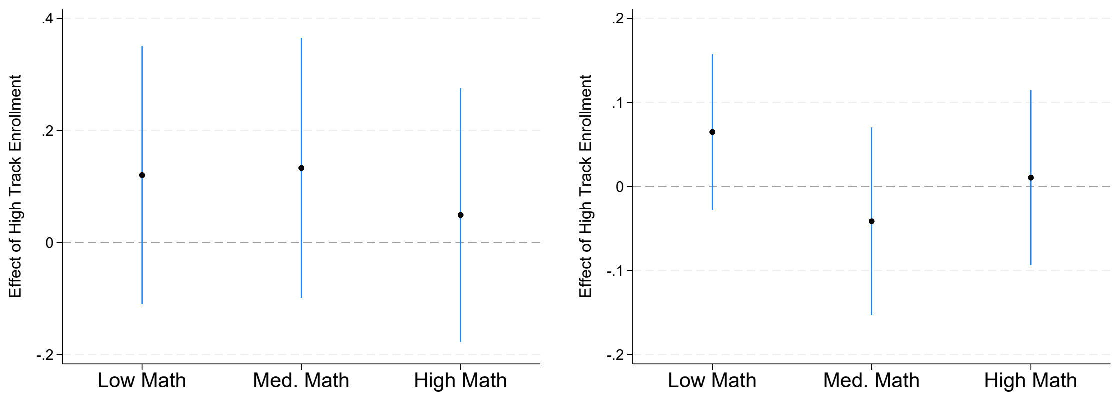
(a) All Tutoring (b) Mathematics Tutoring



Notes: Panel (a) reports the average effect of high-track enrollment on 10th-grade participation in tutoring by gender. Panel (b) reports the effect on mathematics tutoring, in particular. In addition to saturated propensity score and running variable controls, coefficients were estimated controlling for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2).

Figure A.6: Heterogeneous Effects on Tutoring Participation by Baseline Achievement in Mathematics

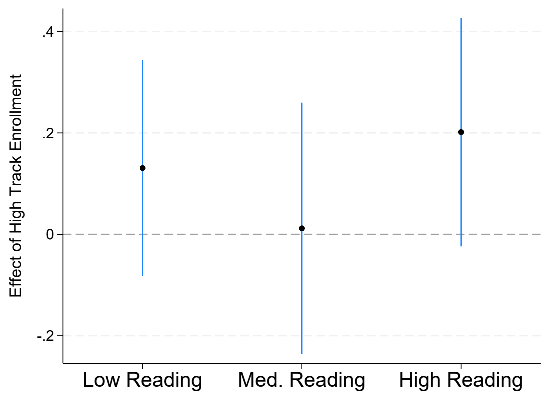
(a) All Tutoring (b) Mathematics Tutoring



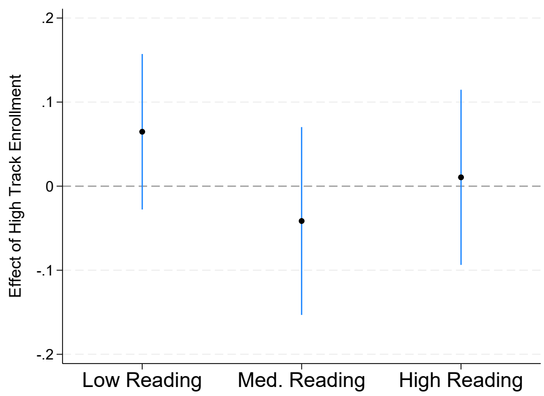
Notes: Panel (a) reports the average effect of high-track enrollment on 10th-grade participation in tutoring by terciled baseline mathematics scores, as measured by standardized 8th-grade test scores. Panel (b) reports the effect on mathematics tutoring, in particular. In addition to saturated propensity score and running variable controls, coefficients were estimated controlling for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2).

Figure A.7: Heterogeneous Effects on Tutoring Participation by Baseline Achievement in Reading

(a) All Tutoring



(b) Mathematics Tutoring

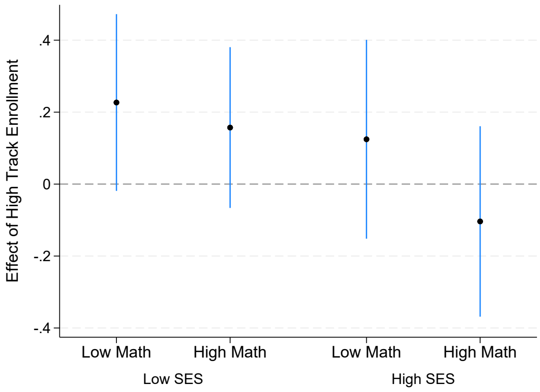


Notes: Panel (a) reports the average effect of high-track enrollment on 10th-grade participation in tutoring by terciled baseline reading scores, as measured by standardized 8th-grade test scores. Panel (b) reports the effect on mathematics tutoring, in particular. In addition to saturated propensity score and running variable controls, coefficients were estimated controlling for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2).

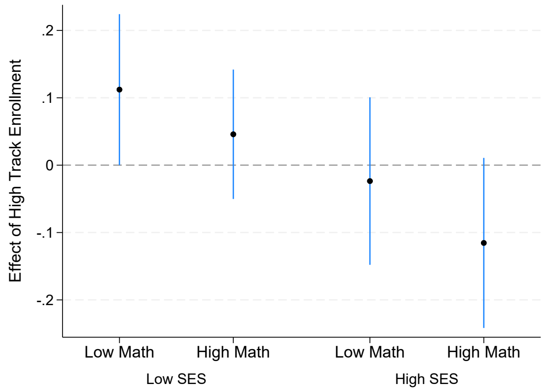
Figure A.8: Heterogeneous Effects on Tutoring Participation under Joint SES and Baseline Achievement Restrictions

(a) Whole Sample

i. All Tutoring

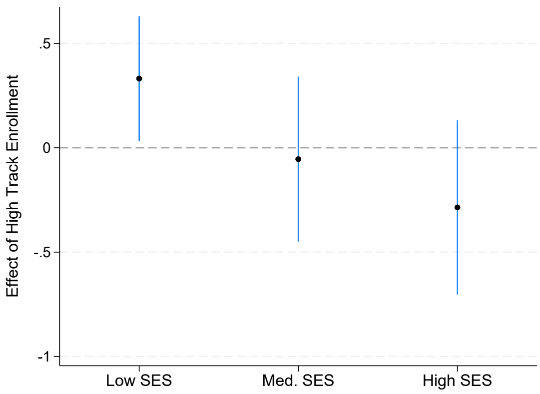


ii. Mathematics Tutoring

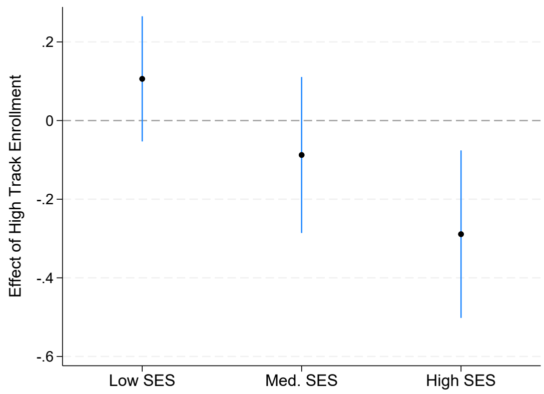


(b) 2nd-8th Deciles of Achievement Only

i. All Tutoring



ii. Mathematics Tutoring



Notes: For i. all tutoring and ii. mathematics tutoring, respectively, Panel (a) of Figure A.8 reports the average effect of high-track enrollment on 10th-grade participation in tutoring by above and below median SES and above and below median ability, where ability is measured in terms of 8th-grade standardized mathematics test scores. Panel (b) restricts the 8th-grade standardized mathematics achievement distribution, by eliminating the bottom 20% of students and top 20% of students, and provides estimates by terciled SES (where terciles were determined prior to implementing the aforementioned restrictions). In addition to saturated propensity score and running variable controls, coefficients were estimated controlling for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2).

B Additional Tables

Table B.1: Testing for Selective Attrition

	(1)	(2)	(3)	(4)	(5)
High Track	-0.027	-0.019	-0.020	0.002	-0.002
	(0.027)	(0.027)	(0.027)	(0.037)	(0.037)
R^2	0.414	0.436	0.440	0.542	0.547
N	3,175	3,175	3,175	2,441	2,441
Propensity score FE	✓	✓	✓	✓	✓
RDD controls	✓	✓	✓	✓	✓
Student controls		✓	✓	✓	✓
Baseline test scores			✓	✓	✓
Baseline tutoring				✓	✓
Family-led support					✓

Notes: Table B.1 presents estimates from 2SLS models of high track attendance on sample attrition, where enrollment in a high track program is instrumented with receipt of a high track offer. In the fully saturated model, we control for the propensity score, running variable controls, individual student characteristics, previous baseline test scores in the 8th grade, baseline participation in tutoring, and family-led support (see Table B.2 for further details). The sample is limited to applicants with non-missing baseline test scores. Robust standard errors are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.2: Summary of Control Variables Used in Main Analysis

Category	Var. Name	Notes
Student controls	age	
	gender	
	SES (CSH-Index)	standardized family background index
	deprived neighborhood	scale 1 (worst) - 5 (best)
	single-mother	indicator var
	child-related benefits	indicator var: discounted or free lunch, textbooks, or receipt of govt. child support
	grade retention	indicator var
	parental education	dominance approach for available parent(s), 1 (< primary) to 5 (masters +)
	financial	"compared to other families how well does your family live?", 1 (worst) to 5 (best)
	siblings	indicator var
Baseline test scores	mathematics	standardized 8th-grade tests
	english	standardized 8th-grade tests
Baseline tutoring	mathematics	indicator vars for participation in 6th and 8th-grade, respectively
	foreign languages	indicator vars for participation in 6th and 8th-grade, respectively
	music	indicator vars for participation in 6th and 8th-grade, respectively
	sport	indicator vars for participation in 6th and 8th-grade, respectively
	other	indicator vars for participation in 6th and 8th-grade, respectively
Family-led support*	homework help	frequency parents help with learning or homework, 0 (never) to 5 (every day)
	discuss school	frequency family discusses happenings in school, 0 (never) to 5 (every day)
	discuss reading	frequency family talks about students' current reading, 0 (never) to 5 (every day)
	parent-teacher meetings	frequency parent(s) attend, 1 (almost never) to 4 (almost always)

*Recorded for both the 6th and 8th-grades.

Table B.3: Sample Descriptive Statistics Pre-Track Assignment

	Not Tutored (1)	Tutored (2)	Highly Tutored (3)
Standardized 8th grade test scores (avg.)			
Mathematics	-0.02	0.18	0.28
Reading	-0.03	0.16	0.31
Demographics			
Female (%)	48.05	48.30	53.68
Age (avg.)	16.57	16.54	16.53
SES-CSH Index (avg.)	-0.21	0.14	0.46
Any social benefits (%)	47.53	42.45	37.50
Deprived neighborhood (%)	10.66	8.07	6.07
Single-mother (%)	25.94	27.70	24.14
Parent w/ maturity exam or higher (%)	62.10	76.43	85.55
N	29,013	15,212	10,406

Notes: Table B.3 presents summary statistics for the overall sample based on the 2015 wave of the NABC when students were in the 8th grade. Column (1) refers to students not participating in any form of extra-curricular tutoring. Column (2) refers to students regularly participating in one type of tutoring, in mathematics, languages, music, sports, or other. Column (3) refers to students who participate in more than one type of extra-curricular tutoring.

Table B.4: Sample Descriptive Statistics Post-Track Assignment

	Non-High Track (1)	High Track (2)
Standardized test scores (avg.)		
Mathematics (10th grade)	-0.42	0.37
Reading (10th grade)	-0.48	0.43
Baseline Math (8th grade)	-0.21	0.48
Baseline Reading (8th grade)	-0.27	0.54
Demographics		
Female (%)	42.14	58.29
Age (avg.)	16.59	16.51
SES (CSH-Index) (avg.)	-0.31	0.44
Any social benefits (%)	49.36	36.93
Deprived neighborhood (%)	11.30	6.19
Single-mother (%)	28.90	22.47
Parent w/ maturity exam or higher (%)	59.12	85.30
Degree of tutoring		
Tutored in 1 subject (%)	27.28	41.21
Tutored in more than 1 subject (%)	11.71	25.56
N	30,737	23,849

Notes: Table B.4 presents summary statistics for the overall sample based on the 2017 wave of the NABC when students were in the 10th grade. Column (1) refers to students not matched to a high-track program during the 2015 secondary school admissions cycle. Column (2) refers to students attending a high-track program.

Table B.5: Logistic Regression Results—Participation in Tutoring by Track Type

	Any Tutoring		Mathematics Tutoring	
	Lower Tracks (1)	High Track (2)	Lower Tracks (3)	High Track (4)
8th-grade mathematics	-0.060***	-0.039	-0.402***	-0.589***
	(0.022)	(0.025)	(0.030)	(0.031)
8th-grade reading	-0.005	-0.050*	0.036	-0.037
	(0.023)	(0.026)	(0.031)	(0.032)
8th-grade uni aspirations	0.455***	0.390***	0.357***	0.242***
	(0.031)	(0.044)	(0.043)	(0.056)
Age	-0.078**	0.014	-0.072*	0.108**
	(0.031)	(0.039)	(0.040)	(0.048)
Female	0.106***	0.264***	0.260***	0.113***
	(0.027)	(0.031)	(0.037)	(0.039)
SES (CHS Index)	0.288***	0.265***	0.367***	0.053
	(0.029)	(0.037)	(0.039)	(0.046)
Single-mother	-0.174***	-0.160***	-0.111***	-0.064
	(0.029)	(0.034)	(0.038)	(0.042)
Any social benefits	-0.200***	-0.102***	-0.412***	-0.337***
	(0.028)	(0.030)	(0.037)	(0.039)
Parents' education				
Below primary *(ref. none)*	-0.882	0.000	-0.965	0.000
	(0.856)	(.)	(1.165)	(.)
Primary *(ref. none)*	-0.275	0.531	-1.051*	0.340
	(0.417)	(0.458)	(0.557)	(0.779)
Low track *(ref. none)*	-0.134	0.413	-0.919	0.032
	(0.423)	(0.487)	(0.569)	(0.840)
Intermed. voc. *(ref. none)*	-0.172	0.574	-0.588	0.806
	(0.415)	(0.440)	(0.550)	(0.754)
Maturity *(ref. none)*	0.058	0.682	-0.435	1.128
	(0.418)	(0.443)	(0.553)	(0.756)
Bachelors *(ref. none)*	0.195	0.870*	-0.327	1.187
	(0.421)	(0.448)	(0.557)	(0.760)
Masters *(ref. none)*	0.265	1.058**	-0.591	1.356*
	(0.425)	(0.454)	(0.563)	(0.766)
Deprived neighborhood	-0.134***	-0.258***	-0.183***	-0.085
	(0.043)	(0.058)	(0.062)	(0.075)
Town (*ref. village*)	0.059*	0.149***	0.093**	0.083
	(0.031)	(0.041)	(0.043)	(0.052)
City (*ref. village*)	0.144***	0.311***	0.148***	0.214***
	(0.040)	(0.048)	(0.053)	(0.059)
Capital (*ref. village*)	-0.054	-0.035	-0.196***	-0.296***
	(0.053)	(0.050)	(0.073)	(0.067)
$Pseudo-R^2$	0.050	0.039	0.050	0.047
N	27,047	20,769	27,047	20,769

Notes: Table B.5 presents results from a logistic model for the overall sample based on the 2017 wave of the NABC, when students were in the 10th grade.

Table B.6: Statistical Tests for Balance

	Full Sample (1)	Selected Sample (2)
8th-grade math	0.717***	0.019
	(0.007)	(0.060)
8th-grade reading	0.828***	-0.041
	(0.007)	(0.061)
6th-grade tutoring participation	0.395***	-0.048
	(0.008)	(0.099)
8th-grade tutoring participation	0.388***	-0.052
	(0.008)	(0.092)
Female	0.157***	-0.064
	(0.004)	(0.047)
Age (in years)	-0.087***	0.042
	(0.004)	(0.038)
SES (CSH-index)	0.757***	0.076
	(0.007)	(0.067)
Any social benefits	-0.127***	-0.032
	(0.004)	(0.048)
Deprived neighborhood	-0.048***	-0.022
	(0.002)	(0.026)
Single-mother	-0.065***	-0.025
	(0.004)	(0.045)
Parent w/ maturity exam or higher	0.262***	0.004
	(0.004)	(0.037)
N	51,135	2,518
Propensity score FE		✓
RDD controls		✓

Notes: Table B.6 presents regressions of student characteristics pre-track assignment on an indicator for whether the student was offered a place in a high-track program. Column (1) refers to the full sample. Column (2) refers to the selected sample of "at-risk" students with non-degenerate assignment risk, and controls both for high-track assignment risk and running variables. The bandwidth used to compute this restricted sample is 0.25, as in Bach et al. (2024), with a uniform kernel. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: First-Stage: High Track Program Offers and Accessions

	(1)	(2)	(3)	(4)	(5)
High Track	0.667***	0.659***	0.659***	0.658***	0.658***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
F-statistic	523.149	505.352	505.164	500.482	501.113
N	2,518	2,518	2,518	2,518	2,518
Propensity score FE	✓	✓	✓	✓	✓
RDD controls	✓	✓	✓	✓	✓
Student controls		✓	✓	✓	✓
Baseline test scores			✓	✓	✓
Baseline tutoring				✓	✓
Family-led support					✓

Notes: Table B.7 reports the results of the first-stage, wherein enrollment in the highest track is instrumented with receipt of an offer of a place in a high-track program. In the fully saturated model, we control for the propensity score, running variable controls, individual student characteristics, previous baseline test scores in the 8th grade, baseline participation in tutoring, and family-led support (see Table B.2 for further details). The sample is limited to applicants with non-missing baseline test scores. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Average Effects of High Track Enrollment on 10th Grade Participation in Alternative Measures of Extra-Curricular Tutoring

	(1)	(2)	(3)	(4)	(5)
Panel A: Dep. Var.: Participation in Tutoring (excl. Mathematics)					
High Track	0.119	0.089	0.090	0.102	0.099
	(0.081)	(0.080)	(0.080)	(0.075)	(0.075)
High Track × Low SES	0.241*	0.234*	0.233*	0.226*	0.227*
	(0.095)	(0.095)	(0.096)	(0.089)	(0.089)
High Track × Med. SES	0.026	-0.007	-0.005	0.030	0.023
	(0.101)	(0.101)	(0.101)	(0.095)	(0.095)
High Track × High SES	0.067	0.026	0.027	0.033	0.031
	(0.118)	(0.117)	(0.117)	(0.108)	(0.107)
Panel B: Dep. Var.: Participation in Non-Academic Tutoring					
High Track	0.084	0.063	0.064	0.072	0.071
	(0.055)	(0.055)	(0.056)	(0.052)	(0.052)
High Track × Low SES	0.160***	0.148**	0.143**	0.139**	0.138**
	(0.061)	(0.062)	(0.062)	(0.058)	(0.058)
High Track × Med. SES	0.032	0.013	0.015	0.044	0.043
	(0.071)	(0.072)	(0.072)	(0.068)	(0.067)
High Track × High SES	0.047	0.023	0.028	0.027	0.028
	(0.081)	(0.081)	(0.081)	(0.075)	(0.075)
N	2,518	2,518	2,518	2,518	2,518
Academic tutoring FE	✓	✓	✓	✓	✓
Propensity score FE	✓	✓	✓	✓	✓
RDD controls	✓	✓	✓	✓	✓
Student controls		✓	✓	✓	✓
Baseline test scores			✓	✓	✓
Baseline tutoring				✓	✓
Family-led support					✓

Notes: In addition to saturated propensity score and running variable controls, we iteratively control for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2). The sample is limited to applicants with non-missing baseline test scores. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Statistical Tests for Balance Computed via Local Bandwidth

	Full Sample (1)	Selected Sample (2)
Baseline 8th-grade math test score (std.)	0.717***	0.009
	(0.007)	(0.061)
Baseline 8th-grade reading test score (std.)	0.828***	-0.075
	(0.007)	(0.062)
Female	0.157***	-0.088*
	(0.004)	(0.049)
Age (in years)	-0.087***	0.045
	(0.004)	(0.040)
SES (CSH-index)	0.757***	0.070
	(0.007)	(0.066)
Any social benefits	-0.127***	0.009
	(0.004)	(0.050)
Deprived neighborhood	-0.048***	-0.013
	(0.002)	(0.026)
Single-mother	-0.065***	-0.015
	(0.004)	(0.047)
Parent w/ maturity exam or higher	0.262***	-0.008
	(0.004)	(0.040)
6th-grade tutoring	0.395***	-0.065
	(0.008)	(0.101)
8th-grade tutoring	0.388***	-0.023
	(0.008)	(0.096)
N	51,135	2,272
Propensity score FE		✓
RDD controls		✓

Notes: Table B.6 presents regressions of student characteristics pre-track assignment on an indicator for whether the student was offered a place in a high-track program. Column (1) refers to the full sample. Column (2) refers to the selected sample of “at-risk” students with non-degenerate assignment risk, and controls both for high-track assignment risk and running variables. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: Local Bandwidth Selected Sample: Average Effects of High Track Enrollment on 10th Grade Participation in Extra-Curricular Tutoring

	(1)	(2)	(3)	(4)	(5)
Panel A: Dep. Var.: Participation in Tutoring					
High Track	0.038	-0.009	-0.008	0.044	0.043
	(0.100)	(0.100)	(0.100)	(0.092)	(0.092)
High Track × Low SES	0.170	0.138	0.144	0.165	0.170
	(0.121)	(0.120)	(0.121)	(0.113)	(0.113)
High Track × Med. SES	0.057	0.006	0.001	0.068	0.058
	(0.129)	(0.130)	(0.129)	(0.121)	(0.121)
High Track × High SES	-0.136	-0.171	-0.173	-0.109	-0.106
	(0.149)	(0.150)	(0.150)	(0.135)	(0.135)
Panel B: Dep. Var.: Participation in Mathematics Tutoring					
High Track	0.000	-0.010	-0.010	0.011	0.011
	(0.043)	(0.044)	(0.044)	(0.042)	(0.043)
High Track × Low SES	0.061	0.052	0.060	0.085*	0.089*
	(0.052)	(0.053)	(0.053)	(0.050)	(0.051)
High Track × Med. SES	0.057	0.038	0.032	0.050	0.044
	(0.058)	(0.059)	(0.059)	(0.057)	(0.057)
High Track × High SES	-0.136**	-0.142**	-0.146**	-0.123**	-0.121**
	(0.064)	(0.065)	(0.065)	(0.061)	(0.061)
N	2,272	2,272	2,272	2,272	2,272
Propensity score FE	✓	✓	✓	✓	✓
RDD controls	✓	✓	✓	✓	✓
Student controls		✓	✓	✓	✓
Baseline test scores			✓	✓	✓
Baseline tutoring				✓	✓
Family-led support					✓

Notes: In addition to saturated propensity score and running variable controls, we iteratively control for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2). The sample is limited to applicants with non-missing baseline test scores. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Local Bandwidth Selected Sample: Average Effects of High Track Enrollment on 10th Grade Participation in Alternative Measures of Extra-Curricular Tutoring

	(1)	(2)	(3)	(4)	(5)
Panel A: Dep. Var.: Participation in Tutoring (excl. Mathematics)					
High Track	0.037	0.001	0.002	0.033	0.031
	(0.082)	(0.082)	(0.082)	(0.076)	(0.076)
High Track × Low SES	0.109	0.085	0.083	0.080	0.081
	(0.100)	(0.101)	(0.101)	(0.095)	(0.095)
High Track × Med. SES	-0.000	-0.032	-0.030	0.018	0.013
	(0.103)	(0.104)	(0.103)	(0.097)	(0.097)
High Track × High SES	0.000	-0.029	-0.027	0.014	0.014
	(0.124)	(0.125)	(0.125)	(0.115)	(0.114)
Panel B: Dep. Var.: Participation in Non-Academic Tutoring					
High Track	0.058	0.030	0.032	0.051	0.053
	(0.056)	(0.057)	(0.057)	(0.053)	(0.053)
High Track × Low SES	0.072	0.052	0.048	0.050	0.057
	(0.067)	(0.068)	(0.069)	(0.065)	(0.064)
High Track × Med. SES	0.054	0.038	0.041	0.071	0.069
	(0.071)	(0.071)	(0.071)	(0.066)	(0.066)
High Track × High SES	0.051	0.023	0.029	0.046	0.051
	(0.084)	(0.085)	(0.085)	(0.079)	(0.079)
N	2,272	2,272	2,272	2,272	2,272
Academic tutoring FE	✓	✓	✓	✓	✓
Propensity score FE	✓	✓	✓	✓	✓
RDD controls	✓	✓	✓	✓	✓
Student controls		✓	✓	✓	✓
Baseline test scores			✓	✓	✓
Baseline tutoring				✓	✓
Family-led support					✓

Notes: In addition to saturated propensity score and running variable controls, we iteratively control for student characteristics, baseline test scores in the 8th grade, baseline tutoring participation, and family-led support (see Table B.2). The sample is limited to applicants with non-missing baseline test scores. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C The Deferred Acceptance Algorithm

The student-proposing deferred acceptance (DA) algorithm broadly functions as follows (see Abdulkadiroğlu and Sönmez (2003) for further details):

> *Step 1:* Students propose to their first choice from a predetermined menu of choices. Each program tentatively assigns seats to their proposing students one at a time, in order of priority, until capacity is reached. Any remaining students are rejected.
>
> In general, for any subsequent
>
> *Step k:* Students rejected in the previous round propose to their next-best choice. Each program considers the students it has already tentatively seated along with its new proposers, and tentatively assigns seats one at a time, again in order of priority, until capacity is reached. Any remaining students are rejected.
>
> The DA algorithm terminates when no proposals are rejected and every student is assigned their final tentative assignment.

Per Gale and Shapley (1962), the resulting matches are both stable and student-optimal. Given all students weakly prefer the school they are matched to, there is no justified envy.

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