The Impact of Exam Schools on Disadvantaged Students: Evidence from NYC's Discovery Program*

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Abstract

This paper studies the New York City Department of Education's Discovery Program, an affirmative action policy implemented to increase access to some of New York City's most elite public high schools. The Discovery Program allocates reserve seats at New York City's exam schools to disadvantaged students who successfully complete the course requirements of a summer program. Using a regression discontinuity design and student-level administrative data I estimate the causal impact of exam school admission through the Discovery Program on educational outcomes. I find that while students experience an initial reduction in high school GPA, this negative effect does not persist into later years. Conversely, reserve seat offers increase performance on standardized math test scores. Under a counterfactual school assignment match with no reserve seats, I show that exam school displacement as a result of the Discovery Program has no effect on math scores, but boosts high school GPA. Taken together, these results suggest that the Discovery Program improves outcomes for disadvantaged students, with little to no achievement cost for those displaced by reserve seats.

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A summer program for high-achieving, low-income students gave me a second chance.

—Richard Zhao, Brooklyn Technical High School

At first, I worried that I wasn't worthy of my specialized high school seat. Now, I know better.

—Mariam Musa, Bronx High School of Science

1 Introduction

Increasing access to high-quality education may further economic opportunity for those from underrepresented groups. Selective colleges have the potential to unlock upward social mobility, with attendance increasing students' chances of reaching the top of the income distribution and gaining employment at prestigious firms (Chetty et al., 2025). More generally, colleges and universities attended by students with high pre-college test scores spend far more on instructional resources than those that enroll students with lower prior achievement (Bleemer and Rothstein, 2026). In light of the importance placed on pre-college academic achievement, attending an elite high school could set students on a path to improved long-term outcomes.

Despite the importance of quality education, admissions and attendance at elite high schools and colleges are often stratified by household income and socioeconomic status. Children from high-income families have an admissions advantage at selective private colleges (Chetty et al., 2025), and in large urban K-12 districts, disadvantaged students attend lower-quality schools than students from more advantaged households (Corradini, 2024). To address equity concerns, some institutions adopt affirmative action admission policies, with the aim of increasing diversity whilst maintaining high academic standards. Thus, closing income gaps in selective high school admissions could reduce inequities in long-term economic opportunity through increased human capital and pre-college test scores.

In this paper, I estimate the causal effect of an affirmative action policy implemented to

increase access to some of New York City's most selective public high schools. The district's "specialized" high schools, also known as exam schools, are considered some of the most elite high schools in the country. In addition to being a pipeline to the Ivy League[1], they enroll some of the highest achieving students in the state. Stuyvesant High School has the highest average SAT scores in New York State and routinely ranks as one of the top public schools in the nation (Abdulkadiroğlu et al., 2014). Similarly, the Bronx High School of Science has an average SAT in the 99.9th percentile and has graduated 9 Nobel Laureates.[2]

The admissions process at New York City's exam schools is extremely competitive. Between 25,000 and 30,000 students apply each year in the hope of receiving one of roughly 5,000 offers. This selectivity, in combination with the nature of the admissions process and lack of diversity in the student body, has led to a heated debate over equity in access to these elite schools. As their name suggests, exam schools admit students based on the results of a single, standardized entrance exam. Proponents of this admission system uphold it as a case study in meritocracy, while critics reference persistent racial gaps in not just who is admitted, but who chooses to apply to these schools (Corcoran and Baker-Smith, 2018; Rucinski and Goodman, 2022). In a 2018 effort to make the admissions process more equitable and boost socioeconomic diversity, city leaders expanded the New York City Department of Education (NYCDOE) Discovery Program, a diversity initiative which dates back to the 1970s.

The Discovery Program is a reserve seat policy that allows economically disadvantaged students the opportunity to participate in a summer program leading to admission at one of New York City's specialized high schools. *Ex-ante*, it is unclear how such a policy might impact academic outcomes. Economically disadvantaged students targeted by the Discovery Program could be "mismatched" to an exam school and be less academically prepared upon admission than their peers. This initial gap may progressively widen throughout their high school career and ultimately lead to academic losses (Sander, 2004). Conversely, increasing

[1]Roughly two-thirds of New York City students who attend Harvard, Princeton, or Yale graduated from one of the district's original three public exam schools—Stuyvesant, Bronx Science, and Brooklyn Tech (Dobbie and Fryer, 2014).

[2]Nobel prizes include 7 for work in Physics, 1 in Chemistry, and 1 in Economics.

access to elite high schools can be considered a human capital investment in students from disadvantaged backgrounds. By attending higher quality schools, these students gain exposure to high-achieving peers, participate in a rigorous curriculum, and access more resources for college preparation.

Using student-level administrative data from the New York City Department of Education, I investigate the impact of attending New York City's selective public exam schools on disadvantaged students receiving an offer to participate in the Discovery Program. I find that reserve seat eligibility and exam school attendance result in achievement gains in standardized test scores. These gains are entirely driven by increases in math test scores. The reduced-form effect of receiving a Discovery Program invite increases PSAT math scores by 17 percent of a standard deviation (σ). Students initially experience a negative effect of exam school admission on grade point average (GPA) in ninth grade, but this effect dissipates by the time they finish eleventh grade. The point estimates on math test scores are larger for female students, while the point estimate on the initial drop in GPA is larger for male students. Additionally, students eligible for Discovery are no more likely to enroll in college than their similarly high-achieving, low-income peers who enroll in traditional public high school.

Standardized test score gains in math, and the lack of benefits in reading scores, could be explained by several mechanisms including curriculum-matching (or peer-matching) and a standard peer effect or school value-added model. To test the extent to which the fit between student type and exam school curriculum or peer composition may explain the reduced-form achievement findings, I estimate a regression discontinuity of the change in slope between achievement and entrance exam score at the cutoff. I find no detectable change in slope at the cutoff, providing suggestive evidence that the level effects on test score outcomes are more likely due to school value-added or traditional peer effects.

These findings shed light on the achievement effects for students who benefit from the Discovery Program. However, due to capacity constraints at selective schools, reserving seats

for economically disadvantaged students necessarily requires reallocating seats from those who would have been admitted in the absence of the Discovery Program, implying that there may be a cost to this admissions rule. What is the causal effect of exam school displacement as a result of the Discovery Program? To answer this question, I run a counterfactual assignment match in which no seats are reserved for economically disadvantaged students. Applicants who receive a more preferred offer under this counterfactual relative to their true assignment are "displaced" by Discovery Program. Using the immediate offer admissions cutoffs in a regression discontinuity design, I compare students who were displaced to those who receive the same offer in both assignment matches (and are therefore unaffected by the reserve seat policy), just above and below the actual admission cutoff. I show that applicants displaced by the Discovery Program have higher high school GPAs and generally experience no change in PSAT or SAT scores.

This paper connects to two primary strands of literature. The first strand investigates the impact of school quality, with a focus on selective high schools in the U.S. and abroad.[3] Outside the U.S., school systems often track students into high schools of different types, such as grammar schools in the United Kingdom (Clark, 2010) and government schools in Kenya (Lucas and Mbiti, 2014). Research on selective secondary schools outside the U.S. has found that enrollment results in improved educational outcomes (Clark, 2010; Jackson, 2010; Pop-Eleches and Urquiola, 2013; Ajayi, 2014; Lucas and Mbiti, 2014; Dustan et al., 2017; Luflade and Zaiem, 2024). However, some gains are minor (Lucas and Mbiti, 2014), and may come with unintended negative consequences such as diminished self-perception (Pop-Eleches and Urquiola, 2013) and lengthy commute times (Dustan et al., 2017).

In the U.S. context, there have been several studies focusing on the large urban school districts of Boston, Chicago, and New York City. These districts each have a small number of extremely high-achieving and prestigious public high schools, known as exam schools, that admit students based on some combination of an entrance exam and previous academic

[3] Beuermann and Jackson (2022) conduct a meta-analysis that includes many of these studies and find that, on average, these schools do not translate to student test score gains.

achievement. The majority of these studies have found no effect of exam schools on test scores or college going for students on the margin of admission (Abdulkadiroğlu et al., 2014; Dobbie and Fryer, 2014; Angrist and Rokkanen, 2015; Abdulkadiroğlu et al., 2017; Allensworth et al., 2017; Barrow et al., 2020; Angrist et al., 2023). There are two notable exceptions to this general consensus.[4] Rokkanen (2015) develops a latent factor-based approach to study inframarginal applicants to Boston's exam schools, finding larger achievement gains for students with lower initial abilities. Additionally, recent work by Ellison and Pathak (2025) finds that selective exam schools are not ineffective, but instead implement optimal curricula based on the ability level of the student body. I extend this literature by providing evidence of exam school effects on high-achieving, low-income students in New York City.

The second strand of literature relates to the effect of affirmative action policies. There exists an extensive literature surrounding affirmative action policies in postsecondary education (Belasco et al., 2015; Epple et al., 2008; Arcidiacono et al., 2011, 2015; Arcidiacono and Lovenheim, 2016; Bennett, 2022; Borghesan, 2022; Bleemer, 2022, 2023; Black et al., 2023; Kapor, 2024). Yet, there have been relatively few studies which focus on policies designed to address inequities in educational opportunity for primary and secondary school students.[5] One K-12 context in which affirmative action policies are more prevalent is exam schools. In this area, Barrow et al. (2020) study the place-based affirmative action policy used for admission at Chicago's selective enrollment high schools (SEHS) and find that students from low-socioeconomic neighborhoods experience negative effects of elite school attendance on grades and enrollment in selective postsecondary institutions. Angrist et al. (2023) use this same setting and policy context to provide evidence that Chicago's negative exam school effects are not the result of the "educational mismatch" hypothesis, but instead due to exam school admission diverting applicants away from strong charter schools where they would

[4] Idoux (2026) presents mixed evidence based on which Boston exam school students attend. Admission to O'Bryant, the least selective school, raises math test scores, while admission to the two more selective schools reduces math scores.

[5] Cheng and Weingarten (2025) study the use of race- and gender-based quotas in Toronto's secondary school admissions.

have otherwise been successful.[6] In contrast to Chicago's place-based SEHS admission policy, my setting features an affirmative action admission policy based on students' household socioeconomic status. In K-12 education markets, the eligibility criteria for affirmative action admission systems may contribute to the effectiveness of the policy in terms of diversifying admissions and generating positive educational outcomes for students. I show that, in the context of New York City's exam schools, a reserve seat system based on household SES meaningfully impacts student test scores and grades. Additionally, this paper is the first to study the causal effect of exam school displacement as a result of an affirmative action program.

Overall, I present evidence that affirmative action admission policies at selective high schools can (i) have negative consequences on early course grades that do not persist, (ii) improve student math test scores, and (iii) have minimal displacement effects on achievement outcomes. The remainder of the paper is organized as follows. Section 2 provides institutional details on New York City's exam schools and the Discovery Program. Section 3 describes the data and Section 4 discusses the main econometric framework. Section 5 presents the effect of exam school admission on disadvantaged students. Section 6 examines how the Discovery Program affects applicants displaced by reserve seats. Section 7 concludes.

2 The Discovery Program

The New York City Department of Education provides robust school choice options to its students and their families. Students interested in attending a public high school in New York can take several pathways.[7] The majority of students participate in a two-sided matching market for traditional public schools, whereby the NYCDOE uses a student-proposing deferred acceptance (DA) algorithm to assign each student to a single school. Students sub-

[6] Dur et al. (2020) and Ellison and Pathak (2021) provide evidence on the efficiency of the place-based affirmative action program at CPS.

[7] Students may also attend one of the city's many private or charter schools, which each have their own distinct admissions process.

mit a rank-ordered list (ROL) of up to twelve schools and schools have set criteria by which they rank applicants.[8] Students receive an offer to their most preferred choice for which they are eligible based on each school's rankings of students (Abdulkadiroğlu et al., 2005).

Students interested in attending a public high school may also apply to one or more of the nine specialized high schools in New York City. Stuyvesant High School, The Bronx High School of Science ("Bronx Science"), and Brooklyn Technical High School ("Brooklyn Tech"), referred to as the "Big 3" by Corcoran and Baker-Smith (2018), are the original three specialized high schools and were founded in 1904, 1938, and 1922, respectively. The High School of American Studies at Lehman College, the High School for Math, Science, and Engineering at City College, and the Queens High School for the Sciences at York College were founded in 2002. Staten Island Technical High School was converted to a specialized high school in 2005, and the Brooklyn Latin School opened in 2006 (Abdulkadiroğlu et al., 2014). These eight schools use the Specialized High School Admissions Test (SHSAT) as the sole criterion for admission (making them known as "exam schools").[9] Eighth grade students interested in attending a specialized high school register for the SHSAT in the Fall and submit a rank-ordered list of their preferences over the eight schools (these preferences are distinct from the ROL of up to twelve traditional public schools described above).[10] The SHSAT is also open to ninth grade students. However, the exam for ninth grade applicants is different than that for eighth grade applicants, and the Discovery Program only applies to rising ninth grade students.

Given that these specialized high schools only use the SHSAT to evaluate applicants, this process can be modeled as a serial dictatorship. Students are ranked according to their exam scores and offered a seat at up to one school (Abdulkadiroğlu et al., 2017). The student with the highest exam score receives an offer to their most preferred school. The student with the

[8]Starting with the 2024-2025 application cycle, there is no limit to the number of schools a student can list on their application. More information on the NYCDOE website: https://www.schools.nyc.gov/enrollment/enroll-grade-by-grade/high-school

[9]The ninth specialized high school, Fiorello H. LaGuardia High School of Music & Art and Performing Arts, admits students based on auditions.

[10]Students are not required to rank all eight schools.

second highest score receives an offer to their most preferred school, provided that there is a seat open at that school (if no seat is available, they are considered at their next preferred school), and so on until enrollment at each school is full (Abdulkadiroğlu et al., 2014). This results in a cutoff score for each of the eight schools. Due to changes in the distribution of test scores, student preferences, and number of available seats, these cutoffs vary from year to year.

All eight testing specialized high schools currently hold their own Discovery Program. Students invited to a school's Discovery Program participate in a three to five week summer program, almost always leading to admission at that school (though schools do reserve the right not to accept a student if they feel that completion of the program was not successful). The length, curriculum, and program completion requirements are specific to the school, with most schools requiring 90 percent attendance and 90 percent completion of assignments. For example, students participating in Stuyvesant's Discovery Program take classes in math, science, and humanities that are meant to prepare them for the rigor of the school's curriculum (The Editorial Board, 2024).

Only students who are invited may participate in a school's Discovery Program, and invitation is determined by a set of eligibility criteria. Students are eligible for the Discovery Program if they:

(1) Score within a certain range on the SHSAT (below the regular admissions cutoff score (for any exam school) but above a program (reserve) cutoff specific to each school); and

(2) attend a high-poverty middle school [11] *(or live in a high-poverty area if the student attends a non-public school or is homeschooled); and*

(3) be certified as disadvantaged by meeting at least one of the following requirements:

- *the family receives assistance from the Human Resources Administration (welfare or SNAP benefits)*
- *student is in foster care, is a ward of the state, or is in temporary housing*[12]
- *the child is an English Language Learner or a former English Language Learner within the previous two (2) school years and enrolled in a DOE school for the first time within the last four years*

[11] Economic Need Index (ENI) of at least 60%.
[12] As defined by the McKinney-Vento Act.

- *the family earns less than or equal to the reduced-price lunch income threshold (based on household size)*[13]

Eligible students are considered only for the Discovery Programs of the schools which they listed on their SHSAT registration. Students who are eligible receive an invitation to apply in their offer letter and must submit the completed application to their current school counselor for the DOE to confirm their eligibility.[14]

The seats allocated to students participating in the Discovery Program are reserve seats for disadvantaged applicants. These seats are allocated using the same mechanism as the regular admission seats. In the first round, the deferred acceptance algorithm is run on all applicants to determine immediate offers for non-reserve seats (Faenza et al., 2023). Once the regular admission process has been run and school-specific cutoffs determined, the same mechanism is run on the subset of disadvantaged students scoring below the cutoff for the school with the lowest non-reserve seat cutoff, and this determines invitations for reserve seats. Before this second match is run to determine Discovery invitations, the NYCDOE classifies applicants into three categories: (1) definitely eligible (i.e., considered "disadvantaged" based on student information they already have) (2) definitely not eligible, and (3) might be eligible, but must provide additional information to prove eligibility. All applicants in groups (1) and (3) are considered when running the DA algorithm for Discovery invitations. Once the algorithm is run, one letter is sent out to students in group (1), inviting them to apply, and a separate letter is sent to students in group (3), notifying them that they may be eligible and can submit documentation proving eligibility to apply.[15] The result of this assignment process, displayed in Figure 1, is a second set of cutoffs that determine eligibility for the Discovery Programs of each school.[16] At Stuyvesant, the top-ranked specialized high

[13] According to the USDA Food and Nutrition Service Income Eligibility Guidelines.

[14] See the NYCDOE website for more information on the Discovery Program's eligibility requirements: https://www.schools.nyc.gov/enrollment/enroll-grade-by-grade/specialized-high-schools/discovery-programs

[15] Both letters are shown in the appendix.

[16] Appendix Table A1 displays reserve (Discovery) and non-reserve cutoff scores for each exam school, by application year from 2010-2021.

school, there is a significant gap between the reserve seat and regular seat cutoff scores. At the other end of the rankings, the cutoff gap at Brooklyn Latin is much smaller, but still consists of a substantial difference in exam scores.

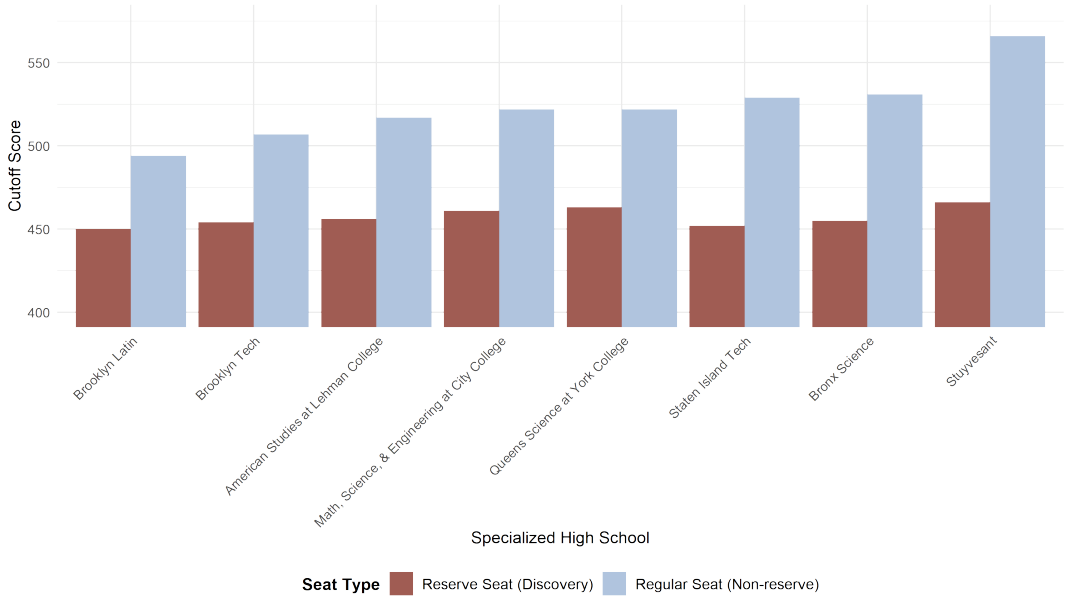


Figure 1: Specialized High School Admission Cutoffs by Seat Type

Notes: This figure shows admission cutoffs for both reserve (Discovery) and non-reserve seats at New York City's specialized high schools in 2019.

Although all eight testing schools currently hold their own Discovery Program, this has only been the case since Summer 2018. Prior to the Fall 2017 application cycle, not all specialized high schools participated in the program.[17] The High School of American Studies at Lehman College, Bronx Science, and Stuyvesant reinstated their programs in 2016, 2017, and 2018 respectively, as the city attempted to increase diversity at the specialized high schools (Hu, 2018). In a subsequent 2018 diversity push, Mayor Bill de Blasio attempted to remove the SHSAT from specialized high school admissions (Shapiro, 2019; Shapiro and Wang, 2019; Rucinski and Goodman, 2022). However, this push by the mayor was widely criticized and failed to gain the necessary support in the state legislature. As an alternative,

[17]The Discovery Program was created in 1971 as part of the Hecht-Calandra Act. Prior to the introduction of the five additional specialized high schools in the early 2000s, the program operated with a different process. Instead of students who scored below the cutoff for any specialized high school, Stuyvesant would admit disadvantaged students who scored just below the Stuyvesant cutoff and Bronx Science would admit disadvantaged students who scored just below their own cutoff (The Editorial Board, 2024).

city leaders expanded the Discovery Program in 2019, and as of 2020, 20 percent of seats at each school are reserved for Discovery students (Zimmer, 2023).

3 Data

I use student-level administrative data from the New York City Department of Education, which contains information on each student's SHSAT score and ROL of specialized high schools, Discovery Program invites and attendance, high school enrollment, demographics, PSAT and SAT test scores, Advanced Placement (AP) test scores, high school GPA, graduation status, and postsecondary enrollment.[18] These files are organized by eighth grade cohort, and contain a unique student identifier to allow linking across files. I briefly discuss the files below and leave additional details for the data appendix.

These records contain information on all eighth grade cohorts applying to exam schools from 2010-11 to 2021-22. For each applicant, I observe a ranking of exam schools and the corresponding admission decision at each ranked school. A student is either accepted, eligible, or not accepted at each school listed on their application.[19] These files also record each applicant's scaled score on the SHSAT.[20] Information on whether or not an applicant is invited to a Discovery Program or attends a Discovery Program is hand-collected by the NYCDOE. Finally, individual school cutoffs for the Discovery Program are provided for each cohort.

Enrollment records contain data on all students attending a New York City Public School (NYCPS). These files include information on the high school at which each student is enrolled, their grade level in that academic year, and demographic characteristics such as race, sex, free or reduced-price lunch status, English language learner status, and special education status. In addition to admission and enrollment records, the NYCDOE files contain

[18] Of course, not all outcomes are available for more recent cohorts. Additionally, some outcomes are not available due to COVID-19 (e.g., the June and August 2020 Regents exams were canceled).

[19] Any applicant eligible for the Discovery Program is not eligible or accepted at any exam school.

[20] The file containing SHSAT scores and preferences over specialized high schools only includes information on students who took the SHSAT in eighth grade.

data on several measures of academic achievement. I focus primarily on PSAT, SAT, and AP scores, as well as GPA in grades 9 and 11. Most students take the PSAT during tenth grade and the SAT in eleventh grade. Every Spring, NYCPS holds a citywide SAT School Day, during which schools provide the SAT to eleventh grade students and the PSAT to tenth grade students at no cost. I standardize both PSAT and SAT scores to be mean zero and have a standard deviation of one within eighth grade application cohort. For students who take a test more than once, I use the section scores corresponding to the attempt with the highest overall score.[21]

Student-level records are supplemented with school-level demographic data from the New York City Open Data Portal.[22] This file contains data on each school's Economic Need Index (ENI), which estimates the percentage of students facing economic hardship. The NYCDOE uses this measure as part of the eligibility criteria for the Discovery Program.

3.1 Descriptive Statistics

Table 1 provides descriptive statistics on exam school applicants and students enrolled in NYCPS in ninth grade. Columns 1 and 2 show the difference in demographic characteristics between students enrolling in exam schools and traditional public schools. The majority of NYCPS students are nonwhite, over three-quarters qualify for free or reduced-price lunch, and almost one-quarter have an Individualized Education Plan (IEP). Although most NYCPS students are Hispanic or Black, ninth grade students at exam schools are predominantly Asian (66 percent) and White (22 percent). These first two columns show that White and Asian students are overrepresented in NYC's exam schools (relative to traditional public schools), while students that are Black, Hispanic, English language learners, or have a disability are underrepresented.

Columns 3 and 4 provide summary statistics of all exam school applicants and those who receive immediate (non-reserve) offers. Consistent with columns 1 and 2, Asian and

[21] Other scores are explored in Appendix Table A5 and discussed in Section 5.3.

[22] This file is provided by the New York City Department of Education and open to the public.

White students are more likely to apply and receive regular offers of admission. Column 5 presents sample means for students that attend a Discovery Program. These students are still disproportionately Asian (70 percent) and male (56 percent), however, they are a more diverse group than those receiving regular offers. Relative to students receiving regular exam school offers, those attending a Discovery program are less likely to be White and more likely to be Black or Hispanic. In particular, reserve seats are aimed at economically disadvantaged students, and 95 percent of Discovery Program attendees are eligible for free or reduced price lunch or have been identified by the Human Resources Administration (HRA) as receiving certain types of public assistance. Column 6 shows the statistics for applicants made worse off by the affirmative action policy by failing to receive an immediate offer or receiving an immediate offer to a less preferred school. These students closely resemble those in column 4, who do receive an immediate offer. Taken together, Table 1 portrays a lack of socioeconomic diversity among exam school applicants, offers, and enrollment, as well as the group differences between regular and reserve seat students.

Table 1: Descriptive Statistics

	NYCPS 9th Graders by School Sector		Exam School Applicants			
	Exam Schools (1)	Traditional Public Schools (2)	All Applicants (3)	Regular Offer (4)	Reserve Seat (5)	Pushed Out (6)
Asian	0.656	0.166	0.381	0.594	0.697	0.580
Black	0.028	0.231	0.156	0.025	0.063	0.039
Hispanic	0.062	0.435	0.235	0.057	0.146	0.080
White	0.220	0.140	0.199	0.282	0.080	0.261
Female	0.439	0.487	0.507	0.465	0.440	0.489
Free/reduced Price Lunch	0.526	0.772	0.642	0.443	0.952	0.487
English Language Learner	0.000	0.115	0.036	0.001	0.007	0.002
Student with Disability	0.017	0.236	0.063	0.020	0.012	0.018
N	17,580	288,108	106,422	18,873	2,735	5,845

Notes: This table presents descriptive statistics for NYC Public School students enrolled in 9th grade as well as applicants to the city's Specialized High Schools for the academic years 2017-18 through 2021-22. The columns distinguish groups of students based on school type or application status. Statistics are computed as means for each group. Columns 1 and 2 present descriptive statistics for NYCPS 9th graders attending exam schools and traditional public schools, respectively. Columns 3 and 4 present those same statistics for all exam school applicants and those that receive an immediate exam school offer, respectively. Columns 5 and 6 report the statistics for applicants affected by the Discovery Program's reserve seat policy. Applicants in column 5 fail to receive an immediate offer to any exam school, and instead occupy a reserve seat through attendance at a summer Discovery Program. Applicants in column 6 would have received an offer to a more preferred school under a counterfactual school assignment match in which there are no seats reserved for Discovery students.

3.2 Analysis Sample

To estimate the effect of the Discovery Program I make several restrictions to the analysis sample. First, records on the Discovery Program do not exist prior to the 2010-11 application cycle and 2017-18 was the first year that all eight testing schools ran Discovery Programs. For these reasons, I restrict my main analysis sample to eighth grade students applying during the Fall 2017 through Fall 2021 application cycles. Second, students that score above the cutoff to receive an immediate offer from the exam school with the lowest cutoff in that application year are ineligible for a reserve seat and excluded from the analysis sample. Finally, the Discovery Program is targeted towards high-achieving, economically disadvantaged students. Ideally, I would restrict the sample to applicants that attend a high-poverty middle school and meet the criteria to be certified as disadvantaged (points (2) and (3) from Section 2), then compare applicants on either side of a reserve seat cutoff. However, the exact eligibility criteria are not observable in the data, therefore, I restrict to students that are (*i*) eligible for free or reduced price lunch or have been identified by the Human Resources Administration (HRA) as receiving certain types of public assistance; or (*ii*) an English Language Learner. I then use the school-level demographic data to exclude students that do not attend a high-poverty middle school.[23][24]

4 Empirical Strategy

To examine the achievement effects of attending an exam school on disadvantaged students, I employ a regression discontinuity design exploiting the discontinuous relationship between exam scores and reserve seat offers of invitation to the Discovery Program. Specifically,

[23]The middle school poverty requirement was added in 2019, meaning this requirement was not binding for students in the Fall 2017 application cohort. However, I make the same sample restriction on this cohort for consistency.

[24]This data limitation is unlikely to affect any causal estimates of the Discovery Program. The criteria not captured in the data (e.g. eligibility based on housing status or previous ELL status) is likely to be highly correlated with the measures that are observed. Additionally, the summary statistics presented in Table 1 and conversations with the NYCDOE suggest that the vast majority of Discovery participants are captured by this sample restriction.

I draw on the "any-offer" design outlined in Abdulkadiroğlu et al. (2017) to estimate an overall exam school sector effect on disadvantaged students. As noted above, the NYC exam school admissions process can be characterized as a serial dictatorship which results in a set of two cutoffs for each school. Let $\tau = (\tau_1, \ldots, \tau_s)$ denote the reserve seat cutoffs at each school $s \in \{1, \ldots, S\}$, r_i the SHSAT score of student i, and ζ the most forgiving cutoff for an immediate (non-reserve seat) offer. If applicants are ranked in descending order of their SHSAT scores, the mechanism assigns disadvantaged applicants to their most preferred school for which they qualify, $\zeta > r_i \geq \tau_s$, and which has an open seat. The any-offer design uses applicant preferences to determine a *qualifying cutoff* for each applicant, the most forgiving (lowest) cutoff in the set of schools a student ranks. If a student clears that cutoff, they will almost certainly receive an invite, to either that school or a more preferred option with a less forgiving cutoff (depending on the applicant's exam score).[25] Formally, denote the set of schools listed on an applicant's ROL as S_θ, then the qualifying cutoff for applicant i is defined as:

$$q_i^* \equiv q^*(\theta_i) = \min_{s \in S_{\theta_i}} \{\tau_s\}$$

Accordingly, the any-offer indicator can be constructed as:

$$D_i = \mathbb{1}[\zeta > r_i \geq q_i^*]$$

Figure 2 shows the distribution of SHSAT scores for all applicants relative to the subsample of disadvantaged applicants, centered on each student's qualifying cutoff. The distribution of disadvantaged applicants has a higher density well to the left of the cutoff, while the distribution of all applicants has a larger spread. This suggests that although, on average,

[25] As discussed in Section 3, the available data does not perfectly align with program eligibility, making it possible that a student clears the qualifying cutoff but does not receive an invitation. Given that the observed and unobserved criteria are presumably highly correlated, this likely occurs infrequently if at all. The NYCDOE cautions that their information on which students receive an invitation to Discovery was collected manually and ad hoc until recently, making analysis of the relationship between the running variable and Discovery invitation subject to measurement error. However, Figure 3 shows that no applicants that fail to clear the qualifying cutoff ever enroll in an exam school in the following year.

disadvantaged students do not perform as well on the SHSAT, those that qualify for the Discovery Program are still in the right tail of both distributions and may be considered high-achieving.

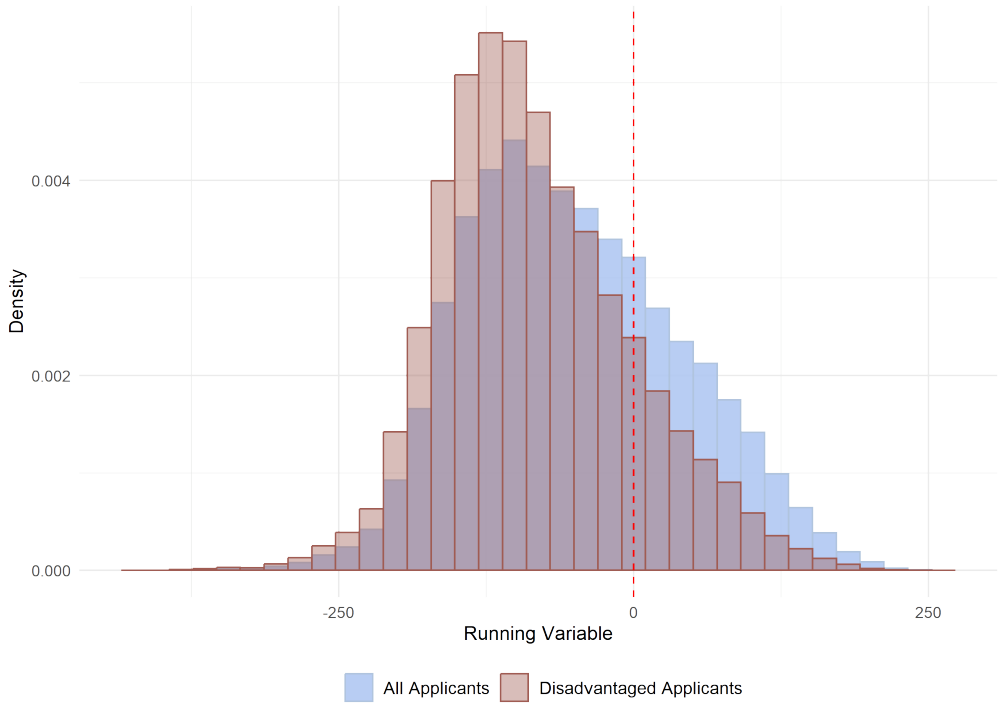


Figure 2: Distribution of centered SHSAT scores

Notes: Applicant exam scores are centered on the school-specific reserve-seat cutoff that determines their qualification for any Discovery Program. The "All Applicants" distribution includes all students taking the SHSAT in Fall of 2017 through Fall of 2021, while the "Disadvantaged Applicants" distribution includes applicants that attended a high poverty middle school in eighth grade and either qualify for free or reduced-price lunch or are English Language Learners (over the same sample period).

The reduced-form estimating equation for the effect of scoring just above the qualifying cutoff can be written as:

$$Y_{ic} = \rho D_{ic} + h(r_{ic}) + \eta_{cq^*} + \varepsilon_{ic} \tag{1}$$

where Y_{ic} is the achievement outcome of applicant i in application cohort c, η_{cq^*} is a set of qualifying-cutoff-by-application-year fixed effects, and ε_{ic} is the individual error term. Finally, $h(r_{ic})$ represents the following running variable control function,

$$h(r_{ic}) = \beta(r_{ic} - q^*_{ic}) + \delta D_{ic} \times (r_{ic} - q^*_{ic}) \tag{2}$$

which is a piecewise local linear specification allowing the slope to change above and below the cutoff. The parameter of interest is ρ, which identifies a reduced-form intent-to-treat (ITT) estimate of scoring just above the program eligibility cutoff. In Section 5.3, I explore robustness to different running variable control functions. In particular, I estimate a quadratic specification for $h(r_{ic})$, as well as a global quartic function following Abdulkadiroğlu et al. (2017) and Angrist et al. (2023).

I estimate a single mean square error-optimal bandwidth for each outcome, selected using the procedure developed by Calonico et al. (2014). Bandwidths are selected using only students eligible for Discovery consideration (i.e., below the most forgiving cutoff for regular admission) and the baseline specification uses triangular weights. Sensitivity to this choice of bandwidth is explored in Section 5.3.

In the context of the New York City school system, there are strong outside options for students not admitted to their specialized high school of choice, for both eligible and ineligible students. As shown in Figure 3, scoring above the qualifying cutoff does not correspond to perfect take-up (attendance/enrollment) among disadvantaged applicants. At the qualifying cutoff, roughly 25 percent of all applicants are enrolled in an exam school in grade 9. Using the analysis sample of disadvantaged students described in Section 3, this jumps to about 50 percent.[26] Figure 3 also shows that, among disadvantaged students, the probability of enrolling in an exam school increases to approximately 75 percent as SHSAT scores rise. The increasing probability of enrollment for disadvantaged students likely reflects the fact that applicants with higher SHSAT scores have more enticing offers and are more willing to accept them.

To account for the fuzziness in grade 9 exam school enrollment at the qualifying cutoff, I use the any-offer indicator as an instrument for exam school enrollment in the following

[26]Specifically, the any-offer first stage for ninth grade exam school enrollment is 0.51. This estimate comes from the sample of students used to compute estimated effects on PSAT math scores in Table 5 below.

two-stage least squares (2SLS) setup:

$$C_{ic} = \gamma_1 D_{ic} + h(r_{ic}) + \phi_{cq^*} + \nu_{ic} \tag{3}$$

$$Y_{ic} = \gamma_2 C_{ic} + h(r_{ic}) + \eta_{cq^*} + \varepsilon_{ic} \tag{4}$$

where C is an indicator for enrollment at any exam school in the year following application and γ_2 represents a local average treatment effect (LATE) for compliers. Consistent with the reduced form estimation, local average treatment effects are estimated using a triangular kernel and qualifying-cutoff-by-application-year fixed effects.

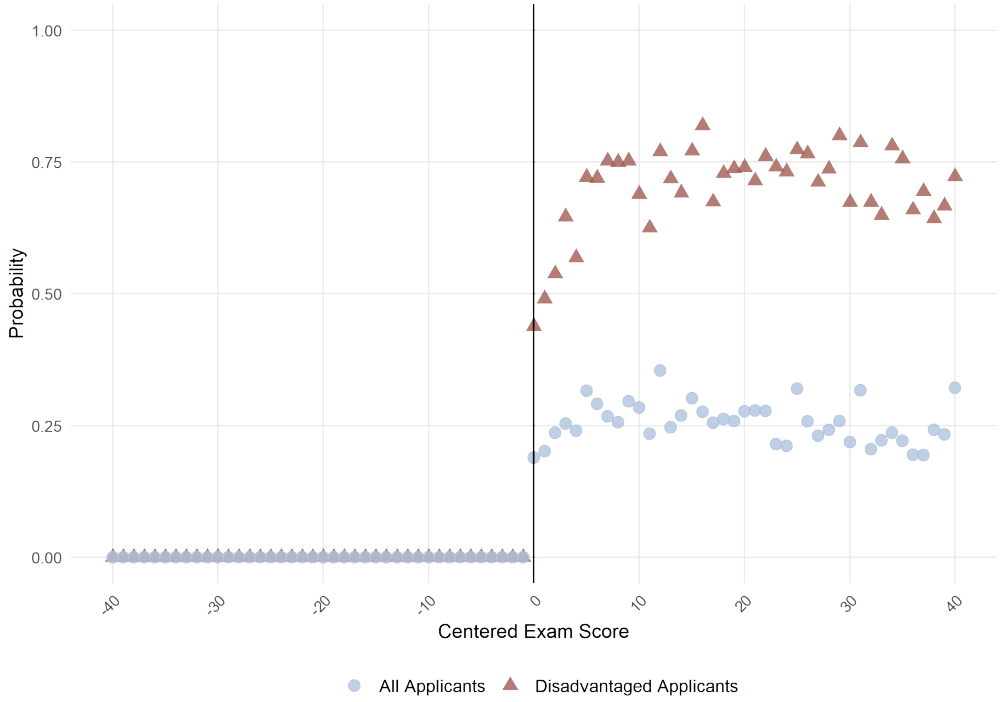


Figure 3: Probability of Enrolling in a Specialized High School

Notes: This figure plots the probability of 9th grade enrollment in any Specialized High School by one-point centered SHSAT bins. Students are centered around their qualifying cutoff, the school on their ROL with the most forgiving cutoff.

4.1 Threats to Identification and Assessment of Validity

In this setting, the identifying assumption is that in the absence of the discontinuity in reserve seat offers that results from the Discovery Program's assignment mechanism, achievement

outcomes would have evolved smoothly through each student's qualifying cutoff. Intuitively, disadvantaged students who score just below the cutoff are reasonable comparisons for students who score just above (Lee and Lemieux, 2010). Accordingly, the counterfactual group is comprised of disadvantaged students who just miss the cutoff for invitation to any Discovery Program, and instead attend a traditional public high school.

In addition to the identifying assumption, there are several conditions which must be met for valid causal inference in a regression discontinuity framework (Schochet et al., 2010). One condition is that the threshold of the forcing variable is not utilized to determine eligibility for programs other than that being studied. In this context, the SHSAT is a test specifically administered to determine admission to these eight specialized high schools and, to the best of my knowledge, serves as a decision rule for no other programs within the NYCDOE.

If students are able to manipulate their test score to be eligible for Discovery Program participation there may be systematic differences between eligible and ineligible students, which would bias the results of estimated treatment effects. Such manipulation is unlikely due to the nature of the assignment mechanism. School-specific cutoffs for both reserve and non-reserve seats are determined *ex post*, meaning that students do not know the relevant cutoffs before taking the exam. As previously discussed, cutoff scores vary from year to year based on student preferences and the distribution of test scores, making exam school offers extremely difficult to game. Additionally, Appendix Table A1 shows that the range of scores that result in a Discovery invitation is narrow and school-specific reserve seat cutoffs are very close (several years show multiple schools with the exact same cutoff score). This implies that manipulating the running variable to result in a reserve seat invitation to a particular school would require scoring within just a few points. Figure A1 shows a density test around the qualifying cutoff following Cattaneo et al. (2018) and suggests no evidence of manipulation.

As an additional check on internal validity, I investigate the smoothness of a number of covariates through the cutoff by using each as an outcome variable in Equation 1 and

present results in Table A2. With the exception of a marginally significant discontinuity in the share of female students, I find no statistically significant discontinuities at the cutoff. The estimates presented below are robust to the inclusion of a set of covariates which includes sex.

5 Results

5.1 Impact Estimates

Figure 4 displays graphical evidence on the effect of clearing the reserve seat qualifying cutoff on the test scores of disadvantaged students. Each panel plots average SAT and PSAT scores in one-point centered SHSAT score bins with local linear fits of the underlying unbinned data. The upper panels depict PSAT and SAT math scores. In the top left, PSAT math scores show a considerable jump at the qualifying cutoff. To the right, SAT math scores also show a jump, though this discontinuity is less pronounced. The lower panels depict PSAT and SAT reading & writing scores. For both the PSAT and SAT, there is no evidence that clearing the cutoff for a Discovery invitation has any effect on reading & writing test scores.

Panel A of Table 2 presents formal estimates of the reduced form effect using Equation 1. For each outcome, the first row corresponds to the "Any Offer" regression discontinuity estimate with robust standard errors in parentheses below, and the third and fourth rows report counterfactual means and sample size, respectively.[27] Test score results are shown in columns 1-4. With respect to PSAT math scores, there is a jump at the cutoff of approximately 0.17σ. Turning to SAT math scores, the jump at the cutoff is a marginally statistically significant 0.08σ. These results are similar in magnitude to Ellison and Pathak (2025), who find that scoring above the Boston Latin School cutoff raises the difference between students' standardized PSAT & SAT scores and their MCAS scores (PSAT-MCAS and SAT-MCAS) by 0.16σ and 0.07σ, respectively.[28] As shown in Figure 4, estimates for

[27] Counterfactual means are defined as the outcome means for students scoring below their qualifying cutoff but within the estimated bandwidth.

[28] The Massachusetts Comprehensive Assessment System (MCAS) is the state's mandatory high school

PSAT and SAT reading are small and not statistically distinguishable from zero. Although this is consistent with much of the exam school literature, it is in contrast to Ellison and Pathak (2025), who find increases in PSAT/SAT and MCAS reading test score gaps of 0.09σ.

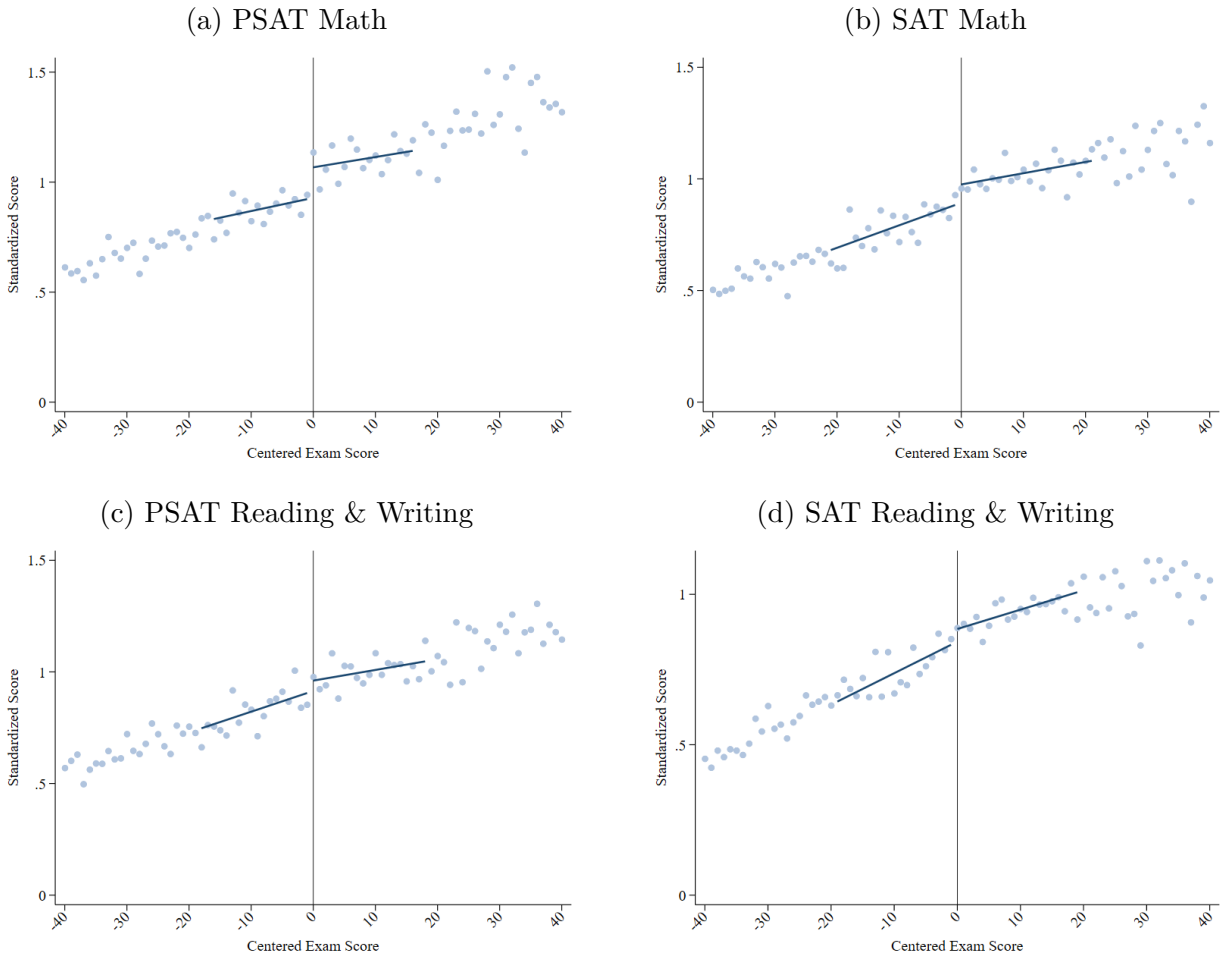


Figure 4: Relationship Between Centered Exam Scores and Standardized Test Scores

Notes: This figure illustrates the effect of being eligible for any Discovery Program on SAT and PSAT scores, by test section. Each panel plots average SAT and PSAT scores in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

Another important academic outcome for students is high school GPA. Despite being an imperfect measure of prior achievement, GPA is used by college admissions offices to evaluate applicants. Consequently, exam school admission may affect postsecondary enrollment and future labor market outcomes through student grades.

graduation exam for the sample period used by Ellison and Pathak (2025).

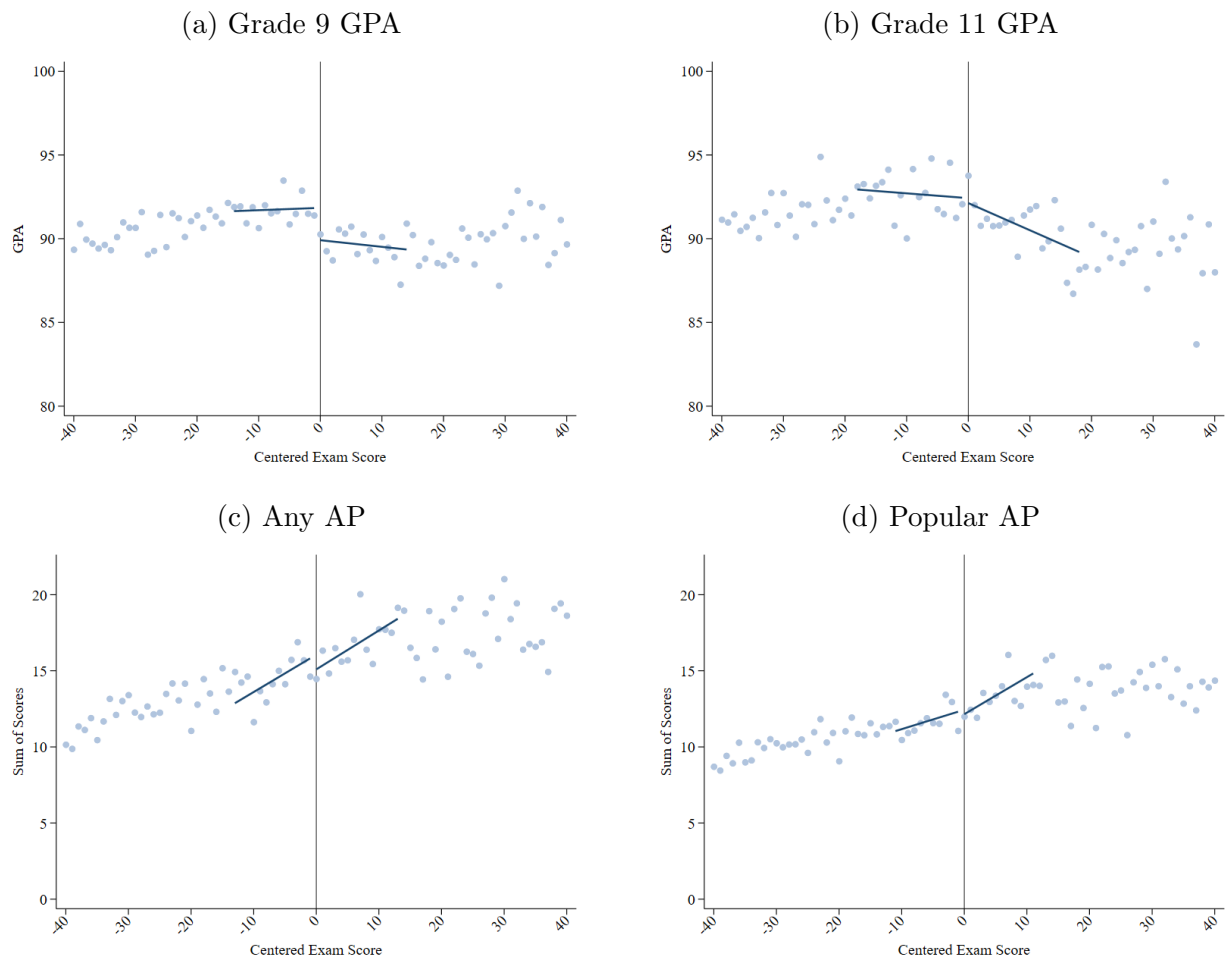


Figure 5: Relationship Between Centered Exam Scores and High School GPA and AP Scores

Notes: This figure illustrates the effect of being eligible for any Discovery Program on GPA in grades 9 and 11, as well as AP exam scores. Each panel plots average outcomes in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

The left panel of Figure 5 shows that students experience a negative impact of Discovery invites on ninth grade GPA.[29] On average, students that score above the qualifying cutoff for a Discovery invite have overall ninth grade GPAs that are 1.9 points lower than disadvantaged students that don't clear the cutoff. This gap translates to approximately 0.08 grade points on a traditional 4.0 scale. Similar to Barrow et al. (2020), this finding may be explained by the fact that students receiving reserve seat offers are mechanically the lowest-achieving students upon enrollment. Despite the summer coursework required

[29]NYCPS reports GPA on a 100-point scale, but values may exceed 100 percent due to weighting of advanced courses (which is at the discretion of the school).

of the Discovery Program, students may still struggle to keep up with the difficulty of the curriculum.[30] However, the right panel of Figure 5 shows that this initial negative impact on GPA dissipates by the time students finish eleventh grade. This result for ninth grade GPA is small relative to Barrow et al. (2020), who find an effect of -0.29 grade points for students from the lowest socioeconomic status (SES) neighborhood that are admitted to a Chicago exam school. These results also contrast their finding of a persistent negative effect on GPA through eleventh grade.

Table 2: Estimates of Discovery Program Achievement Effects

	PSAT		SAT		GPA		AP exams	
	Math	Reading	Math	Reading	Grade 9	Grade 11	All exams	Popular exams
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Reduced form (ITT)								
Any offer	0.165***	0.051	0.075*	0.037	-1.885***	-0.240	-0.922	-0.195
	(0.045)	(0.041)	(0.042)	(0.040)	(0.629)	(0.799)	(1.034)	(0.850)
Counterfactual mean	0.87	0.82	0.77	0.74	91.7	92.7	14.5	11.6
N	3,049	3,406	3,417	3,104	3,146	3,075	1,950	1,633
Panel B: 2SLS (LATE)								
Any offer	0.295***	0.090	0.137*	0.068	-3.664***	-0.467	-2.457	-0.571
	(0.078)	(0.072)	(0.076)	(0.073)	(1.207)	(1.542)	(2.742)	(2.463)
First stage F	501.2	551	472.8	429.6	426.6	387.3	149.5	114.7
N	3,049	3,406	3,417	3,104	3,146	3,075	1,950	1,633

Notes: This table reports reduced form and 2SLS estimates of the Discovery Program for students that applied during the Fall 2017-21 admission cycles. Panel A reports reduced form (ITT) estimates of the effect of scoring above the qualifying cutoff on achievement outcomes. Panel B reports 2SLS (LATE) estimates of exam school enrollment on achievement outcomes. All estimates control for a local-linear function in the running variable and all outcome-specific bandwidths are estimated via the procedure developed by Calonico et al. (2014). The table also shows mean outcomes for students to the left of the cutoff in Panel A and first stage F statistics for the 2SLS estimates in Panel B. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Prior literature has noted the high rate of AP test-taking among students enrolled in exam schools in Boston and New York (Abdulkadiroğlu et al., 2014; Ellison and Pathak, 2025). AP courses offer college-level curriculum to high school students, who are then tested

[30] Coull (2019) writes that "My struggles in the Discovery Program say a lot about its authenticity. As a current freshman at Stuyvesant, I am struggling with the same things I was then. I had difficulty following the curriculum for biology and math during the program, and I continue to struggle in those classes... These two subjects specifically have gotten me stuck because the curriculum is on a collegiate level... The intense workload from all my classes prevents me from devoting enough time to math and biology... As a student, I'm not sure that my participation in the Discovery Program aided my transition to Stuyvesant. It may have gotten me accustomed to the Stuyvesant way of things so that I wasn't surprised during September. However, I am definitely struggling more than I'd like to be, and even more than I did in the Discovery Program. This makes sense because now it's the real thing. Expectations, stress, strain, and workload have been dumped on me from the first day of school and have become progressively worse as the school year goes on and the end of the first semester approaches."

on their knowledge of the course material. AP exams are scored on a scale of 1-5, and college credits are often granted for scores of at least 3 or 4. Following Abdulkadiroğlu et al. (2014), I estimate the AP effect using the sum of scores over all AP exams taken by a student.

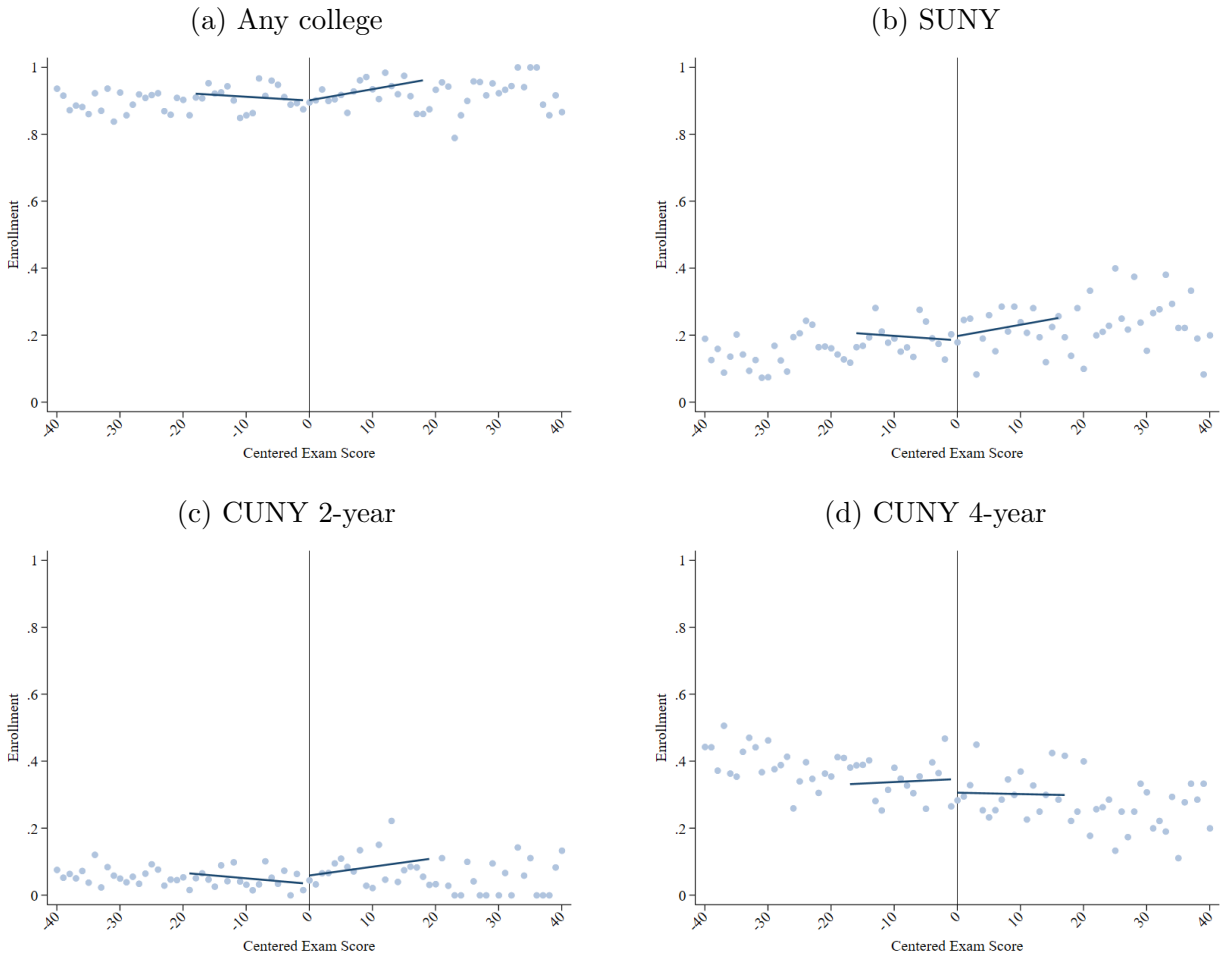


Figure 6: Relationship Between Centered Exam Scores and Postsecondary Enrollment

Notes: This figure illustrates the effect of being eligible for any Discovery Program on postsecondary enrollment. Each panel plots mean enrollment in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

Columns 7 and 8 of Table 2 report estimates for the sum of scores on all exams as well as the sum of scores on a subset of the most popular AP exams.[31] Estimates are noisy and show no effect of Discovery invites on AP exam scores, for either all exams or popular courses.

[31] The most popular exams include Biology, Chemistry, Calculus AB, Computer Science Principles, English Language and Composition, English Literature and Composition, Environmental Science, Macroeconomics, Physics 1, Psychology, Spanish Language and Culture, Statistics, United States Government and Politics, United States History, and World History.

The reduced form estimates indicate that reserve seat offers affect standardized test scores in math as well as early high school GPA. Panel B of Table 2 reports 2SLS estimates of Equation 4, which represent the LATE for compliers at the qualifying cutoff. Consistent with an enrollment first stage of about 0.5, students that attend the Discovery Program and enroll in an exam school have PSAT math scores that are 0.3σ higher, on average, than students that just miss their qualifying cutoff and enroll in a traditional NYCPS.[32] As with the reduced form estimates, there is a marginally significant effect on SAT math scores. For compliers, the magnitude of this effect is 0.13σ. Additionally, exam school enrollment reduces ninth grade GPA by 3.7 grade points (approximately 0.15 points on a 4.0 scale). For eligible students that ultimately decide to attend a Discovery Program and enroll in an exam school, there are substantial math test score gains. Consistent with the reduced form estimates, I find no effect on eleventh grade GPA or AP exam scores.

Table 3: Estimates of Discovery Program Postsecondary Enrollment Effects

	Any college (1)	CUNY 2-year (2)	CUNY 4-year (3)	SUNY (4)
Panel A: Reduced form (ITT)				
Any offer	0.001	0.021	-0.029	0.010
	(0.027)	(0.018)	(0.044)	(0.039)
Counterfactual mean	0.91	0.05	0.35	0.19
N	2,256	2,351	2,142	2,030
Panel B: 2SLS (LATE)				
Any offer	0.002	0.040	-0.056	0.021
	(0.052)	(0.035)	(0.086)	(0.078)
First stage F	296.1	312.1	276.5	246.2
N	2,256	2,351	2,142	2,030

Notes: This table reports reduced form and 2SLS estimates of the Discovery Program for students that applied during the Fall 2017-21 admission cycles. Panel A reports reduced form (ITT) estimates of the effect of scoring above the qualifying cutoff on achievement outcomes. Panel B reports 2SLS (LATE) estimates of exam school enrollment on achievement outcomes. All estimates control for a local-linear function in the running variable and all outcome-specific bandwidths are estimated via the procedure developed by Calonico et al. (2014). The table also shows mean outcomes for students to the left of the cutoff in Panel A and first stage F statistics for the 2SLS estimates in Panel B. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

The results presented in Table 2 show that students scoring high enough to be eligible

[32]First stage estimates vary slightly based on bandwidth, which is estimated separately for each outcome.

for Discovery have higher PSAT and SAT math scores. Higher standardized test scores may translate to increases in college enrollment. To test this, I estimate the effect of Discovery eligibility on postsecondary enrollment outcomes. Figure 6 indicates that the Discovery Program had no effect on college enrollment. This may be unsurprising given that the vast majority of students scoring this high in the SHSAT distribution enroll in college after finishing high school, while very few enroll in a 2-year CUNY program. Although the estimate is not statistically significant, the sign on enrollment in a 4-year CUNY program is negative, which could be driven by substitution to more selective colleges. Unfortunately, this is not testable without more detailed information on college enrollment patterns.

5.2 Heterogeneity

In this section, I explore whether exam schools have heterogeneous impacts on male and female students. Splitting the sample, Table 4 reports estimates of equation 1 separately for subsamples of male and female students. In the sample of female students, there is a large jump in PSAT math scores at the qualifying cutoff (shown in Appendix Figure A2). The estimates reported in column 1 suggest that female students who clear their qualifying cutoff experience a 0.2σ increase in PSAT math scores. For male students, the point estimate is a smaller but meaningful 0.12σ. Turning to SAT math scores, clearing the qualifying cutoff is associated with an 0.11σ increase (statistically significant at the 10 percent level) for female students. The corresponding point estimate for male students, 0.04σ, is positive but not distinguishable from zero. I find no effect of reserve seat eligibility on PSAT or SAT reading scores for male or female students.

Next, I break down exam school effects on GPA and AP exam scores. Male students experience a reduction of 1.94 grade points, which is similar to the main estimate of 1.89 points reported in Table 2. For female students, there is a reduction in grade 9 GPA of 1.3 points. However, this estimate is not statistically significant. Estimates on grade 11 GPA for male and female students are not statistically distinguishable from zero. Again, I find

no effect on AP exam scores. Lastly, consistent with the null findings reported in Table 3, panel B of Table 4 shows that the Discovery Program has no effect on college enrollment for male or female students.

Table 4: Reduced Form Heterogeneity by Sex

	Female			Male		
	Estimate (1)	Mean (2)	N (3)	Estimate (4)	Mean (5)	N (6)
Panel A: Achievement outcomes						
PSAT math	0.201***	0.79	1,533	0.124**	0.96	1,763
	(0.061)			(0.062)		
PSAT reading	0.073	0.87	1,533	0.039	0.76	2,054
	(0.058)			(0.056)		
SAT math	0.110*	0.75	1,470	0.038	0.85	1,565
	(0.062)			(0.062)		
SAT reading	0.068	0.77	1,470	0.007	0.72	1,351
	(0.053)			(0.069)		
Grade 9 GPA	-1.342	93.2	1,363	-1.938**	89.9	2,101
	(0.824)			(0.829)		
Grade 11 GPA	0.120	94.1	1,361	-0.223	91.1	1,317
	(1.040)			(1.369)		
All AP exams	0.321	15.2	913	-2.054	13.7	1,042
	(1.439)			(1.520)		
Popular AP exams	1.345	12.5	953	-0.744	10.7	1,163
	(1.088)			(1.053)		
Panel B: Postsecondary enrollment outcomes						
Any college	-0.020	0.93	938	0.037	0.89	1,378
	(0.037)			(0.039)		
CUNY 2-year	0.017	0.04	938	0.023	0.05	1,156
	(0.019)			(0.033)		
CUNY 4-year	-0.026	0.32	1,051	-0.016	0.4	1,315
	(0.064)			(0.057)		
SUNY	-0.019	0.18	1,152	0.043	0.19	1,036
	(0.052)			(0.052)		

Notes: This table presents reduced form (ITT) estimates exploring heterogeneity by applicant sex. Column 1 reports estimates of Equation 1 on a sample restricted to female applicants and column 4 reports estimates on a sample restricted to male applicants. For each subsample, outcome-specific bandwidths are re-estimated using the procedure developed by Calonico et al. (2014) after splitting the sample. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

5.3 Robustness

This section presents a series of analyses to assess the robustness of the main findings presented in Table 2. I start by presenting estimates using alternative bandwidths. These symmetric bandwidths range in one-point SHSAT intervals from 10 to 40. Appendix Figures A8 and A9 depict point estimates and 95 percent confidence intervals from the preferred specification using Equation 1 with triangular weights. These estimates are in line with the main result presented in Table 2. One exception is that AP exam scores seem to converge to zero and slightly reverse sign as the bandwidth increases. It is worth noting that the number of students taking AP courses is small relative to the full population of NYCPS students, and the sample size for AP outcomes in Table 2 is less than two-thirds the sample size of test score and GPA outcomes.

Appendix Table A3 reports first stage, reduced form (ITT), and 2SLS (LATE) estimates using a uniform kernel. Estimates on PSAT and SAT scores in math are slightly smaller while the estimate on grade 9 GPA is slightly more negative. However, all estimates are qualitatively similar to those presented in Table 2. Appendix Table A4 presents reduced form estimates from alternative specifications of the running variable controls. Columns 1-4 report estimates using a local linear function of the running variable controls and various fixed effects. Column 5 reports estimates of Equation 1 with the addition of several covariates including indicators for whether a student is Female, Black, Hispanic, or Asian. Indicators for each borough of residence (using Manhattan as the reference category) are included as well. Adding these covariates does not add much precision to the test score estimates but does slightly attenuate them. Column 6 reports estimates using a quadratic relationship between the running variable and each outcome. Column 7 reports estimates using a global quartic function of the following form:

$$h(r_{ic}) = \sum_{p=0}^{4} \phi_p r_{ic}^p \tag{5}$$

and allows for polynomial coefficients that are fixed over the support of the running variable. These estimates are less precise than those using local linear controls.

Students may take the PSAT and SAT more than once, and it is possible that the choice of score may influence estimation results. Appendix Table A5 presents reduced form estimates using alternative choices of PSAT and SAT scores. Panel A reports the main estimates found in Table 2, these use the section scores that are associated with each student's maximum total standardized test score. Motivated by the fact that most four-year colleges evaluate applicants using their SAT superscore, in Panel B I use the highest PSAT and SAT section scores for each student regardless of whether those section scores were attained on different attempts (Goodman et al., 2020).[33] Estimates using PSAT and SAT superscore are very similar to those using the maximum scores. Finally, Panel C uses each student's first attempt on each test. The estimate on SAT math scores is slightly smaller than those using the maximum and superscores. The estimate on PSAT math drops from 0.17σ using the preferred maximum score to 0.1σ using the first attempt (and this estimate is statistically significant at the 5 percent level relative to 1 percent for the maximum and superscore outcomes). This may suggest that exam schools provide some additional motivation to improve initial scores on important standardized tests.

Collectively, these robustness checks provide consistent evidence that clearing the qualifying cutoff for reserve seat eligibility has meaningful impacts on PSAT math scores and grade 9 GPA. The estimates are quantitatively and qualitatively similar across various specifications and bandwidths.

5.4 Curriculum-matching or School Value-added?

Figure 1 illustrates the fact that the Discovery student experience is not homogeneous. While many students who attend the Discovery Program at Brooklyn Latin are relatively close to the school's regular cutoff, those who attend Stuyvesant's Discovery Program differ

[33] Goodman et al. (2020) point out that roughly 75 percent of four-year colleges use applicants' maximum score, and over 80 percent of those institutions define that maximum as the superscore.

substantially in prior achievement to their peers who receive immediate offers. Furthermore, Ellison and Pathak (2025) show that curriculum-matching (or peer matching) in exam schools can play an important role in identifying which students realize achievement gains from attendance. What role does match quality play in the achievement effects of the Discovery Program?

The fit between exam school curricula and student type may change abruptly at the cutoff, resulting in a discontinuity in the derivative of the relationship between student entrance exam score and future achievement (Ellison and Pathak, 2025).[34] Visually, Figure 4 shows little evidence of any meaningful change in slope at the cutoff. To formally assess this, I follow Ellison and Pathak (2025) and estimate the change in slope of the relationship between PSAT and SAT performance and entrance exam scores at the qualifying cutoff using Equation 1. The first row of Table 5 shows the level differences in achievement at the qualifying cutoff that were explored in Section 5.1. The second row of Table 5 presents estimates of δ in Equation 1, representing the change in slope at the qualifying cutoff. I find no detectable evidence of slope changes at the cutoff. Estimates for both math and reading are close to zero and not statistically significant. This provides suggestive evidence that the level effects on math test scores are inconsistent with models of curriculum or peer quality matching, and may be attributable to traditional peer effects or school value-added.

This finding also suggests that Discovery students who just clear their qualifying cutoff for a reserve seat invitation gain just as much as those who score high enough to receive an invitation to a more selective reserve seat program, which is inconsistent with the mismatch hypothesis. However, this result is suggestive and should be interpreted cautiously, as there may be offsetting forces which result in a lack of slope change at the qualifying cutoff.[35]

[34]Perhaps equally relevant in this context, Ellison and Pathak (2025) note that a similar model of peer effects could be the mechanism behind changes in slope at the cutoff. Particularly if disadvantaged students are positively impacted by exposure to high-achieving exam school peers, as in a traditional peer effects framework, but experience negative consequences that stem from a disparity between their ability and the average ability of their peers.

[35]There is also the added difficulty of separating slope changes from non-linear relationships between the running variable and achievement outcomes.

Namely, the nature of the any-offer design implies that as students move further above their qualifying cutoff, the more likely they are to receive an offer to the Discovery Program of a more selective exam school. Thus, in contrast to Ellison and Pathak (2025), above the cutoff, match quality decreases as students are exposed to more advanced peers and curricula. However, this downward pressure may be at odds with the prediction of Ellison and Pathak (2025), whereby students above the cutoff become better suited to a rigorous exam school curriculum than the traditional public school alternative.

Table 5: Changes in Levels and Slope at the Qualifying Cutoff

	PSAT		SAT	
	Math	Reading	Math	Reading
	(1)	(2)	(3)	(4)
Change in level at cutoff (ρ)	0.165***	0.051	0.075*	0.037
	(0.045)	(0.041)	(0.042)	(0.040)
Change in slope at cutoff (δ)	0.000	-0.002	-0.003	-0.002
	(0.005)	(0.004)	(0.004)	(0.004)
Counterfactual mean	0.87	0.82	0.77	0.74
N	3,049	3,406	3,417	3,104

Notes: This table reports estimates of changes in levels and the slope of achievement outcomes at the qualifying cutoff. All estimates control for a local-linear function in the running variable and all outcome-specific bandwidths are estimated via the procedure developed by Calonico et al. (2014). The table also shows mean outcomes for students to the left of the cutoff. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

6 Exam School Displacement

Affirmative action admission policies aim to address inequities in access to selective schools, where demand for enrollment far exceeds the supply of seats. At highly sought after high schools, enrollment is fixed, implying that affirmative action policies stratify applicants into two groups. One group of applicants is "Pulled In" and benefits from such policies by receiving an offer of admission that they otherwise would not have in the absence of the policy, while the other group of applicants is "Pushed Out" and fails to receive the offer that they would have in the absence of the policy (Black et al., 2023). A limited number of seats at

selective schools implies that affirmative action admission policies necessarily allocate seats to applicants in the former group by diverting them from applicants in the latter.

Understanding the implications of affirmative action for students that are Pushed Out is of consequence for several reasons. Selective schools are often in demand due to the high academic achievement of their students, and both the short and long-term benefits to attendance can be substantial. Students that are pushed out of their more preferred option may enroll in schools with lower baseline peer achievement. The difference in peer exposure and overall school quality may translate to lost achievement gains. Second, by pulling one group of students in while pushing another group out, an affirmative action admission policy can dramatically alter the peer composition of selective schools. This change in peer composition has the potential to impact peer effects and human capital generation in selective schools. Lastly, the high-achieving students who are pushed out of more selective schools may generate positive peer effects at a less selective school. However, these same students may decide to exit the traditional public school sector in favor of an outside option such as private or charter schools.

In this section, I examine how the Discovery Program affects applicants in the Pushed Out group. To do so, I run a counterfactual assignment in the absence of the Discovery Program. Recall that seats at NYC's exam schools are allocated in two stages. In the first stage, the DA algorithm is run on all applicants to generate immediate offers and in the second stage the same algorithm is run on a subset of eligible (and potentially eligible) applicants to determine reserve seat invitations. For each application year, I count the number of immediate offers and the number of students attending the Discovery Program at each school to back out the total seat capacity of each exam school.[36] Using these total enrollment caps, I run the first stage of the match assignment described above, allocating all seats based on the full sample of applicants and not reserving seats for disadvantaged students. Each applicant is assigned up to one offer under the counterfactual of no reserve

[36] Appendix Figure A11 shows the trend in immediate offers contrasted with that of reserve seat attendance in the Summer Discovery Program at each of the "Big 3" exam schools.

seats. If an applicant's actual offer is not the same as the counterfactual offer, that student is classified as being in the Pushed Out group of the exam school to which they received an offer under the counterfactual assignment.

Each reserve seat can generate a cascade of displacement through the mechanism. For example, suppose that student i is on the margin of admission to Stuyvesant, their first choice. In the absence of any reserve seats, they receive an offer of admission. However, when seats are diverted to reserve, applicant i is "pushed out" of Stuyvesant and receives an offer to Bronx Science, their second choice. Student i thus displaces student j from Bronx Science, and so forth. In this way, many students are not Pushed Out of all exam schools, but simply bumped down to a less preferred option.

6.1 Descriptive Analysis

Table 6 presents the Specialized High School enrollment patterns of applicants in the Pushed Out group. The eight columns represent the eight schools that applicants receive an offer from under the counterfactual assignment without reserve seats. Panel A reports the probability of enrolling in each exam school. For example, row 2 of column 1 corresponds to the probability of enrolling in Brooklyn Tech, conditional on being pushed out of Stuyvesant. Several interesting patterns emerge. First, 85 percent of applicants pushed out of Stuyvesant enroll in another Specialized High School. This likely reflects the fact that Stuyvesant is routinely ranked first on ROLs and admits the highest-scoring applicants. Students for whom counterfactual assignment is Stuyvesant have likely scored high enough on the SHSAT to secure an offer to another SHS that is preferred to any outside option. A similar story could be told of Bronx Science, another highly ranked school, and the enrollment destination for 36 percent of the students pushed out of Stuyvesant. There is also a large fraction of students pushed out of the High School of Mathematics, Science and Engineering at City College, Queens High School for the Sciences at York College, and Staten Island Technical High School. These schools have a much smaller seat capacity than the Big 3, which results in

capacity being reached quickly among high-scoring applicants.

Table 6: Pushed Out Enrollment Patterns

	Counterfactual offer							
	Stuyvesant (1)	Brooklyn Tech (2)	Bronx Science (3)	MSE City College (4)	Lehman College (5)	Queens Science (6)	Staten Island Tech (7)	Brooklyn Latin (8)
Enrollment								
Stuyvesant	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.109
Brooklyn Tech	0.284	0.013	0.435	0.482	0.284	0.470	0.687	0.086
Bronx Science	0.354	0.004	0.000	0.049	0.000	0.000	0.000	0.043
MSE City College	0.045	0.000	0.069	0.000	0.000	0.000	0.021	0.008
Lehman College	0.007	0.000	0.118	0.079	0.000	0.022	0.000	0.004
Queens Science	0.030	0.002	0.083	0.018	0.014	0.000	0.000	0.014
Staten Island Tech	0.125	0.005	0.000	0.000	0.000	0.000	0.000	0.013
Brooklyn Latin	0.002	0.20	0.004	0.018	0.066	0.009	0.000	0.004
Any SHS	0.847	0.236	0.709	0.646	0.364	0.501	0.708	0.281
N	536	2,321	696	164	211	230	335	1,351

Notes: This table presents enrollment patterns and demographic characteristics of students pushed out of an exam school. Each column corresponds to the exam school that a student would have received an offer to in the absence of the reserve seat policy. In Panel A, each row corresponds to the proportion of students in each column that enroll in a particular school. In Panel B, each row corresponds to the proportion of students in each column with that characteristic. The sample consists of all applicants in the Fall 2017 through Fall 2021 cycles for whom their actual seat assignment is different from their counterfactual seat assignment.

Another pattern to emerge from Table 6 is that Brooklyn Tech, the largest Specialized High School, is a landing ground for many of the applicants pushed out of other Specialized High Schools. Of the students pushed out of Staten Island Tech, almost 70 percent enroll in Brooklyn Tech. Over 40 percent of students displaced from Bronx Science, MSE at City College, and Queens Science also enroll in Brooklyn Tech. Lastly, it is worth noting that 11 percent of applicants pushed out of Brooklyn Latin, the school with the lowest cutoff, go on to enroll in Stuyvesant, the school with the highest cutoff. Many of the students displaced from Brooklyn Latin fail to enroll in another exam school. However, economically disadvantaged applicants pushed out of Brooklyn Latin are actually at the top of the distribution of students considered for reserve seats. This results in students failing to receive an immediate offer to any exam school, but instead receiving a reserve seat offer at their first choice school.

The distribution of assignment preferences can be seen in Table 7, which reports the probability of receiving an offer to a student's first choice school, conditional on being pushed

out of each preference ranking. The probability of a first choice offer increases from 2 percent of students pushed out of their first choice school to 39 percent of students pushed out of their eighth choice school. The reserve seat system is designed to allow economically disadvantaged students who score just below the cutoff for admission to any school the chance to participate in a summer course before enrolling in a Specialized High School. By targeting high-achieving, low-income students on the margin of admission to one or more of the lower ranked Specialized High Schools, students at the high end of the reserve-eligible distribution actually receive much better offers than in the counterfactual admission system with no reserve seats. Relatedly, less than 10 percent of students who attend a Discovery Program are displaced from a traditional exam school offer, suggesting that the admissions policy does not simply reshuffle disadvantaged students from less selective to more selective exams schools.

Table 7: Distribution of Assignment Preferences

	Counterfactual rank							
	1st (1)	2nd (2)	3rd (3)	4th (4)	5th (5)	6th (6)	7th (7)	8th (8)
Actual rank								
1st	0.017	0.051	0.101	0.138	0.159	0.233	0.301	0.394
2nd	0.522	0.000	0.000	0.004	0.006	0.000	0.010	0.000
3rd	0.122	0.370	0.000	0.000	0.006	0.000	0.015	0.000
4th	0.057	0.103	0.172	0.000	0.000	0.000	0.000	0.000
5th	0.035	0.054	0.090	0.136	0.000	0.000	0.000	0.000
6th	0.014	0.027	0.064	0.085	0.129	0.000	0.000	0.000
7th	0.008	0.027	0.054	0.068	0.058	0.073	0.000	0.000
8th	0.006	0.015	0.024	0.028	0.036	0.026	0.024	0.000

Notes: This table presents a matrix of Specialized High School preference rankings. Columns represent the preference ranking of the school that a student would have received an offer to in the absence of the reserve seat program, while rows represent the ranking of the school they actually received an offer to attend.

As previously mentioned, the reserve seat system results in a cascade of displacement that affects some applicants differently than others. In particular, not all students are pushed out of all exam schools. Table 7 shows a probability matrix of counterfactual offer and actual

offer preference rankings. The second row of column 1 suggests that 52 percent of students pushed out of their first choice school receive an offer to their second choice school. Students pushed out of their second choice have a 37 percent chance of receiving an offer to the third choice school. This pattern continues down the counterfactual preference rankings, where we see that only 2 percent of students pushed out of their seventh choice receive an offer to their eighth choice. This pattern also reflects the fact that not all students rank all eight schools.

6.2 Displacement Effects

How does exam school displacement affect achievement outcomes? To answer this question, I use each school's immediate offer cutoff in a regression discontinuity and compare students who are in the Pushed Out group to those who score just above the cutoff. For each school, I restrict the sample to applicants who receive an offer under the counterfactual assignment with no reserve seats. Applicants in this group who score below the actual cutoff are in the Pushed Out group at that school. Applicants who score above the cutoff receive an offer under both actual and counterfactual seat assignments, and are therefore unaffected by the reserve seat admission system.[37] The formal reduced-form estimating equation can be expressed as follows:

$$Y_{ic} = \alpha_1(r_{ic} - \mu_s) + \alpha_2 \mathbb{1}(r_{ic} < \mu_s) \times (r_{ic} - \mu_s) + \psi \mathbb{1}(r_{ic} < \mu_s) + \pi_c + \varepsilon_{ic} \tag{6}$$

where μ_s is the immediate offer cutoff for school s, π_c is an application cohort fixed effect, and $\mathbb{1}(r_{ic} < \mu_s)$ is an indicator for scoring below the cutoff at school s. The parameter

[37] Appendix Figures A14 and A15 show the probability of offers and enrollment at the big 3 exam schools at the cutoff. Figure A14 shows that, in the restricted subsample for each school, realized offers are deterministic at the cutoff. Panel a of Figure A15 shows that students displaced from Bronx Science and Stuyvesant never enroll in those schools, whereas some who are displaced from Brooklyn Tech are able to enroll through the Discovery Program. At each school, the probability of enrollment jumps significantly at the cutoff. Panel b of A15 shows enrollment at any exam school at each of the Big 3 cutoffs. At Stuyvesant, there is a very small discontinuity in enrollment at any school at the cutoff, while there is a large jump in the probability of enrollment in any exam school at the Brooklyn Tech cutoff.

of interest is ψ, which represents the impact of being pushed out of exam school s on the outcome of interest.

The running variable for each school-level analysis is mechanically bounded below by the centered exam score of the lowest scoring applicant in the Pushed Out group.[38] I use these to manually construct a symmetric bandwidth around each school's immediate offer cutoff.[39] Triangular weights are applied for each school-specific estimation. Appendix Figures A12 and A13 show running variable density tests at each school, and Appendix Table A6 reports school-level RD estimates of Equation 6 using covariates as outcomes.

Table 8 reports reduced form RD estimates of being in the Pushed Out group at Stuyvesant, Bronx Science, and Brooklyn Tech. In contrast to the results presented in Section 5, I find no effect of exam school displacement on standardized math scores.[40] With the exception of a reduction for students in the Pushed Out group at Bronx Science, I find null effects on standardized reading scores. However, columns 5 and 6 suggest that Pushed Out applicants have higher GPAs in grades 9 and 11. This GPA effect is particularly strong for students in the Pushed Out group at Stuyvesant, the most selective exam school. Surprisingly, students displaced from Stuyvesant have improved AP exam outcomes, while the sign on the estimates from Bronx Science and Brooklyn Tech goes the other direction.

Panel B of Table 8 presents displacement estimates on college enrollment. Relative to the mean (of students to the right of the cutoff, whose offers are unaffected by the reserve seat program), there is a small effect of displacement from Stuyvesant and Bronx Science on enrollment in any college. Additionally, applicants who are pushed out of Bronx Science are more likely to enroll in a SUNY program. For all three schools, I find null effects of displacement on CUNY enrollment.

[38] This is equivalent to each school's immediate offer cutoff under the counterfactual school assignment match with no reserve seats.

[39] Bandwidths are 12 SHSAT points for Stuyvesant, 15 for Bronx Science, and 16 for Brooklyn Tech. In comparison, bandwidths for the main analysis in Section 5 are 16 for PSAT Math and Reading outcomes.

[40] This finding is consistent with the Ellison and Pathak (2025) curriculum-matching model, but does not rule out achievement effects that account for curriculum differences (such as the difference between state-level standardized test scores and PSAT/SAT scores). Unfortunately, the NY State Regents exams were canceled or waived for several cohorts in my analysis sample, making this analysis infeasible.

Table 8: Estimates of Displacement Effects on Achievement

	Stuyvesant			Bronx Science			Brooklyn Tech		
	Estimate (1)	Mean (2)	N (3)	Estimate (4)	Mean (5)	N (6)	Estimate (7)	Mean (8)	N (9)
Panel A: Achievement outcomes									
PSAT math	-0.084	2.03	1,206	-0.029	1.74	1,572	-0.014	1.47	4,166
	(0.057)			(0.063)			(0.036)		
PSAT reading	0.069	1.83	1,206	-0.054	1.61	1,572	0.046	1.38	4,166
	(0.046)			(0.047)			(0.028)		
SAT math	-0.047	1.79	951	-0.058	1.62	1,313	0.037	1.34	3,494
	(0.047)			(0.053)			(0.034)		
SAT reading	0.050	1.76	951	-0.087*	1.58	1,313	0.013	1.35	3,494
	(0.047)			(0.048)			(0.030)		
Grade 9 GPA	4.400***	91.78	1,262	1.131*	92.79	1,706	1.629***	92.32	4,516
	(0.536)			(0.622)			(0.409)		
Grade 11 GPA	4.840***	92.14	971	2.077**	93.53	1,357	3.770***	94.13	3,562
	(0.826)			(0.873)			(0.606)		
All AP exams	6.447***	25.85	942	-2.429*	27.81	1,300	-1.314	22.29	3,084
	(1.863)			(1.304)			(0.909)		
Popular AP exams	6.938***	16.1	930	-0.733	19.92	1,283	-1.574**	18.06	3,066
	(1.211)			(0.933)			(0.688)		
Panel B: Postsecondary enrollment outcomes									
Any college	-0.068*	0.97	712	-0.083*	0.95	1,021	0.025	0.87	2,645
	(0.040)			(0.046)			(0.025)		
CUNY 2-year	-0.017	0.02	712	0.016	0.01	1,021	-0.020	0.03	2,645
	(0.012)			(0.017)			(0.012)		
CUNY 4-year	-0.015	0.08	712	-0.046	0.14	1,021	-0.013	0.17	2,645
	(0.055)			(0.045)			(0.031)		
SUNY	-0.097	0.25	712	0.136**	0.2	1,021	-0.027	0.23	2,645
	(0.065)			(0.059)			(0.033)		

Notes: This table presents reduced form (ITT) estimates of exam school displacement, corresponding to Equation 6, for students that applied during the Fall 2017-2021 admission cycles. School-level analysis samples are restricted to applicants within 12 centered exam score points of the cutoff for Stuyvesant, 15 points for Bronx Science, and 16 points for Brooklyn Tech. For each school, the analysis samples are restricted to applicants who receive an offer under the counterfactual assignment with no reserve seats. Triangular weights are applied for each school-specific estimation. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Focusing on the impact estimates at Brooklyn Tech provides potential insight into displacement from the exam school sector, as only 24 percent of students in the Pushed Out group at Brooklyn Tech go on to enroll in another exam school. Estimates on PSAT and SAT scores are all small and not statistically distinguishable from zero. Failing to clear the cutoff and being displaced from Brooklyn Tech leads to a 1.6 grade point increase in grade 9 GPA that more than doubles to 3.8 in grade 11. These results imply that applicants who would have received an offer to Brooklyn Tech in the absence of the Discovery Program experience no change in standardized test scores or college enrollment but face some combination of

more lenient grading and a less rigorous curriculum.

7 Summary and Conclusions

New York's elite specialized high schools are often considered a contentious topic. Although they boast extremely high average SAT scores and send their graduates to some of the most prestigious colleges in the country, these schools have historically served a student body that lacks socioeconomic diversity. In 2019, city leaders took steps to address this inequity by increasing the number of seats reserved for students from economically disadvantaged households. The expansion of the Discovery Program provided the opportunity to study the effect of an affirmative action policy that reserves seats at prestigious secondary schools based on household socioeconomic status. Affirmative action style policies are rare in primary and secondary school settings. However, as more public school districts seek to increase choice options and decrease educational inequities, understanding which policy designs effectively increase socioeconomic diversity while improving student outcomes is crucial.

To understand the consequences of a reserve seat policy that sets eligibility criteria based on applicants individual household socioeconomic characteristics, I use the setting of New York City's specialized high schools. I find evidence that reserve seats at exam schools negatively impact ninth grade GPA for disadvantaged students on the margin of admission. However, this negative effect on GPA does not persist in later grades. In contrast, I find that the Discovery Program improves math test score outcomes. Both reduced form and 2SLS estimates suggest considerable increases in PSAT math scores, and smaller but meaningful gains in SAT math scores. Heterogeneity analyses suggest that achievement gains in math test scores are considerably larger for female students. Additionally, I show that performance on SAT and PSAT scores is unaffected by exam school displacement as a result of the Discovery Program.

Overall, my findings indicate that disadvantaged students benefit from an admissions policy designed to increase access to NYC's elite specialized high schools. These results

suggest that affirmative action admission policies based on household socioeconomic status may increase diversity at elite public high schools and translate to achievement gains for disadvantaged students, with little cost to those displaced by reserve seats.

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Online Appendix to:

The Impact of Exam Schools on Disadvantaged Students: Evidence from NYC's Discovery Program

Michael Darisse

October 15, 2026

A Appendix Figures and Tables

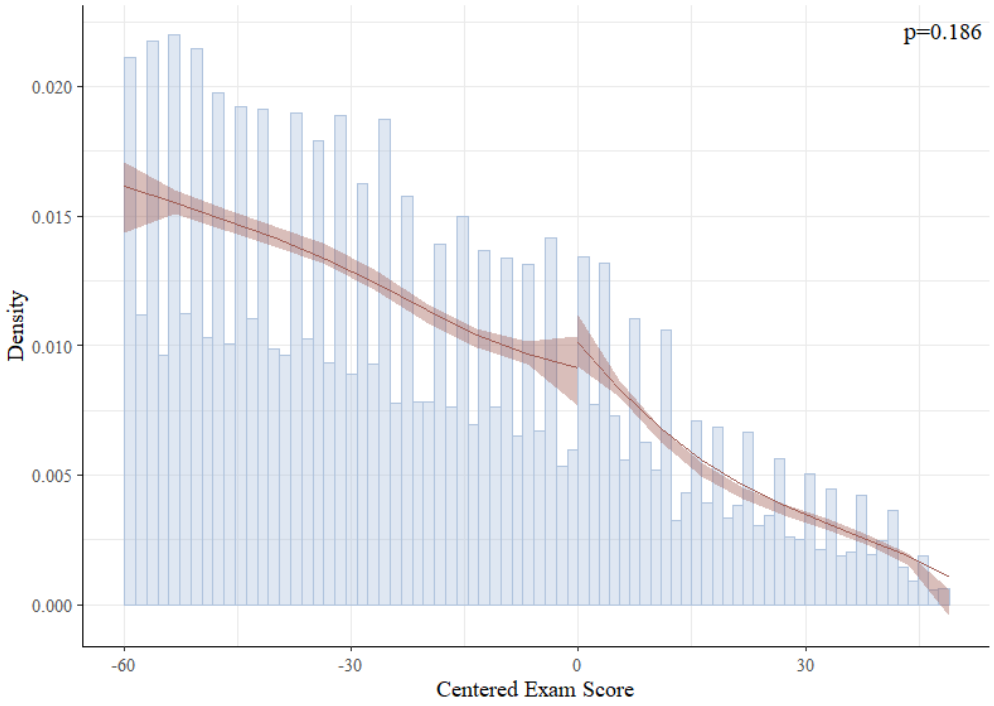


Figure A1: Running Variable Density Plot

Notes: This figure shows a density test around each student's qualifying cutoff following Cattaneo et al. (2018). A p-value of 0.186 suggests a failure to reject the null hypothesis of no manipulation around the cutoff. The sample is restricted to students that attended a high poverty middle school in eighth grade and either qualify for free or reduced-price lunch or are English Language Learners.

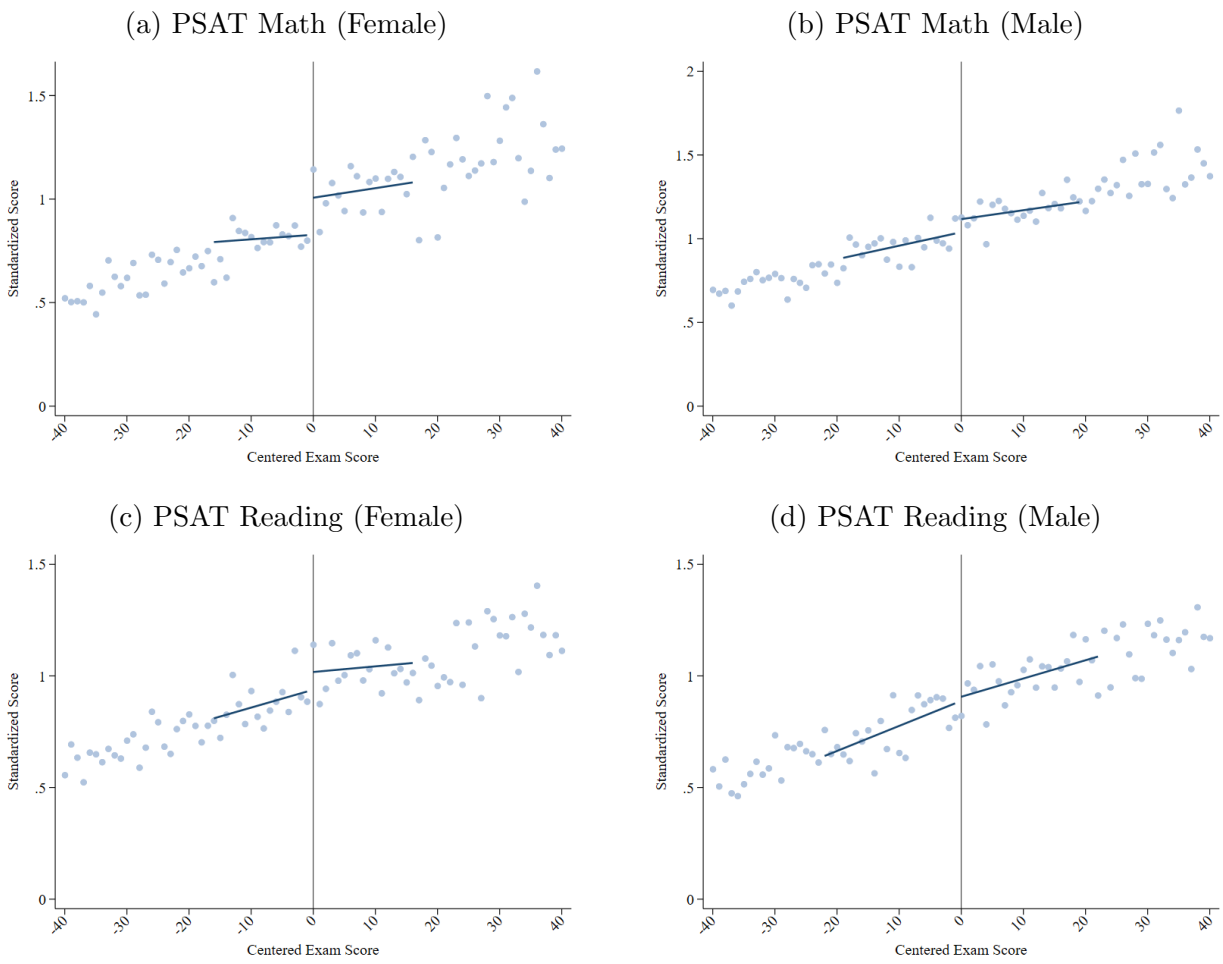


Figure A2: PSAT Heterogeneity by Sex

Notes: This figure illustrates the effect of being eligible for any Discovery Program on PSAT scores. Panels a and c on the left show the effect on PSAT scores for female students and Panels b and d on the right show the effect for male students. The top two panels report grade PSAT math results and the bottom panels report PSAT reading results. Each panel plots average PSAT scores in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

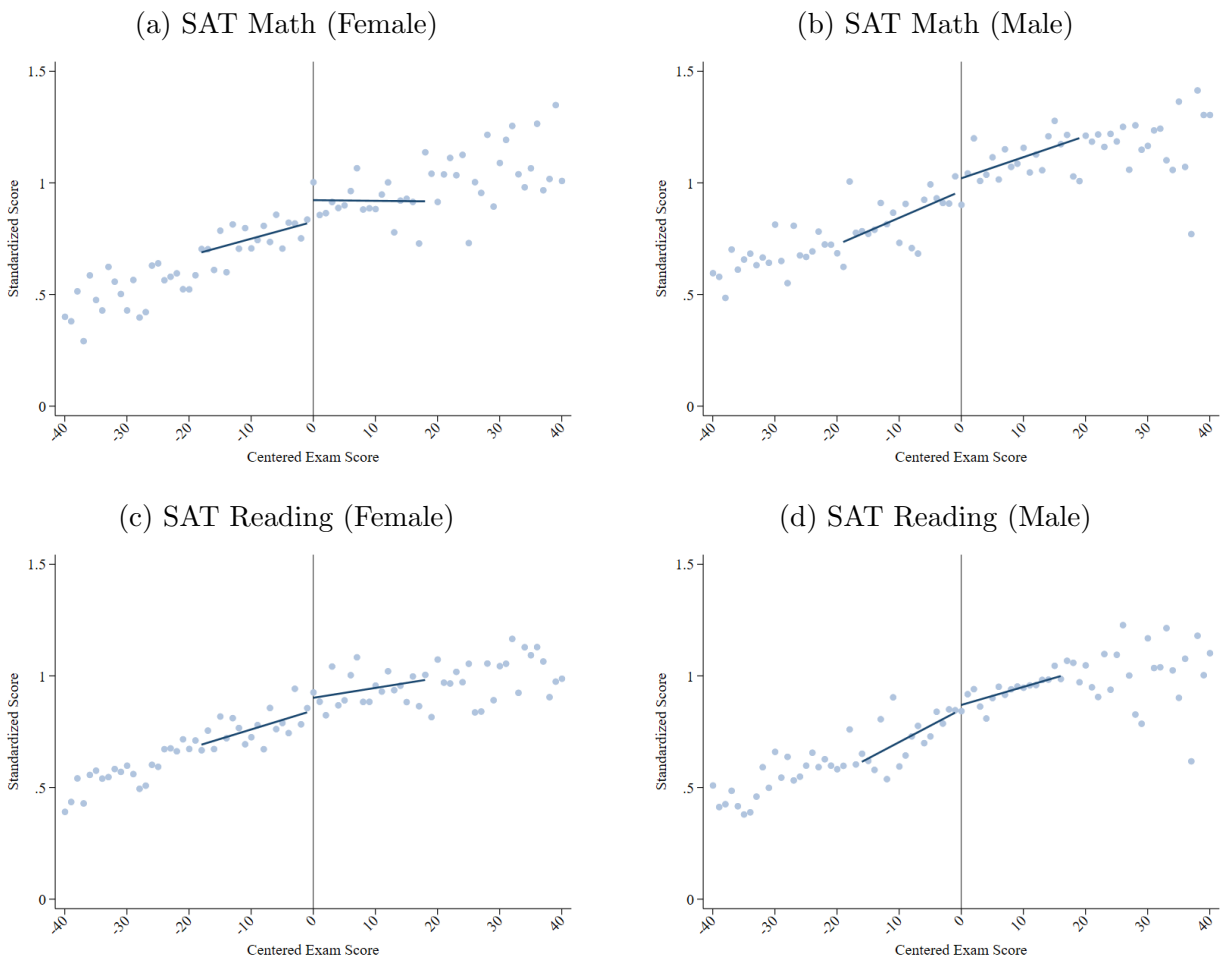


Figure A3: SAT Heterogeneity by Sex

Notes: This figure illustrates the effect of being eligible for any Discovery Program on SAT scores. Panels a and c on the left show the effect on SAT scores for female students and Panels b and d on the right show the effect for male students. The top two panels report grade SAT math results and the bottom panels report SAT reading results. Each panel plots average SAT scores in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

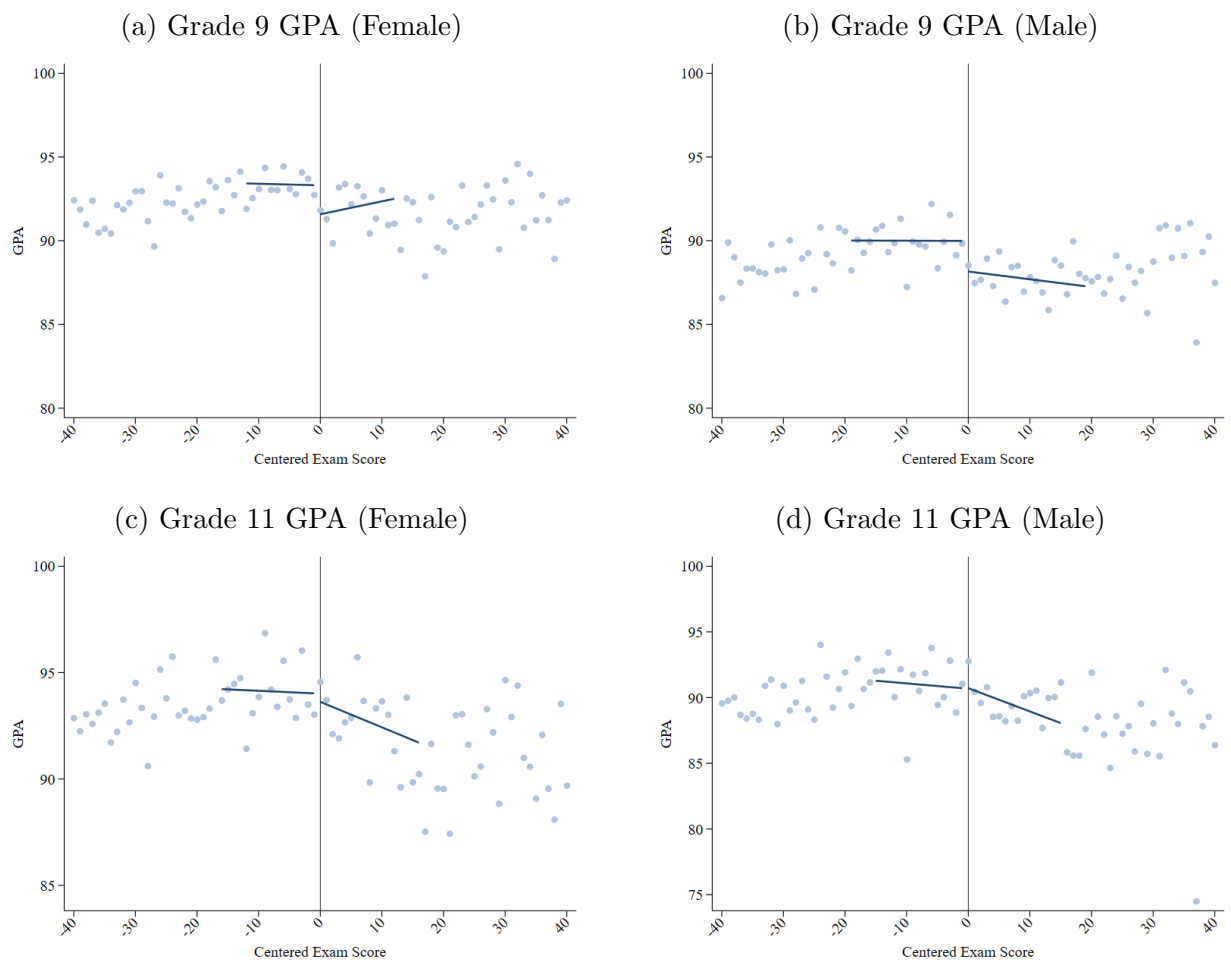


Figure A4: GPA Heterogeneity by Sex

Notes: This figure illustrates the effect of being eligible for any Discovery Program on GPA in grades 9 and 11. Panels a and c on the left show the effect on GPA for female students and Panels b and d on the right show the effect for male students. The top two panels report grade 9 GPA results and the bottom panels report grade 11 GPA results. Each panel plots average GPA in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

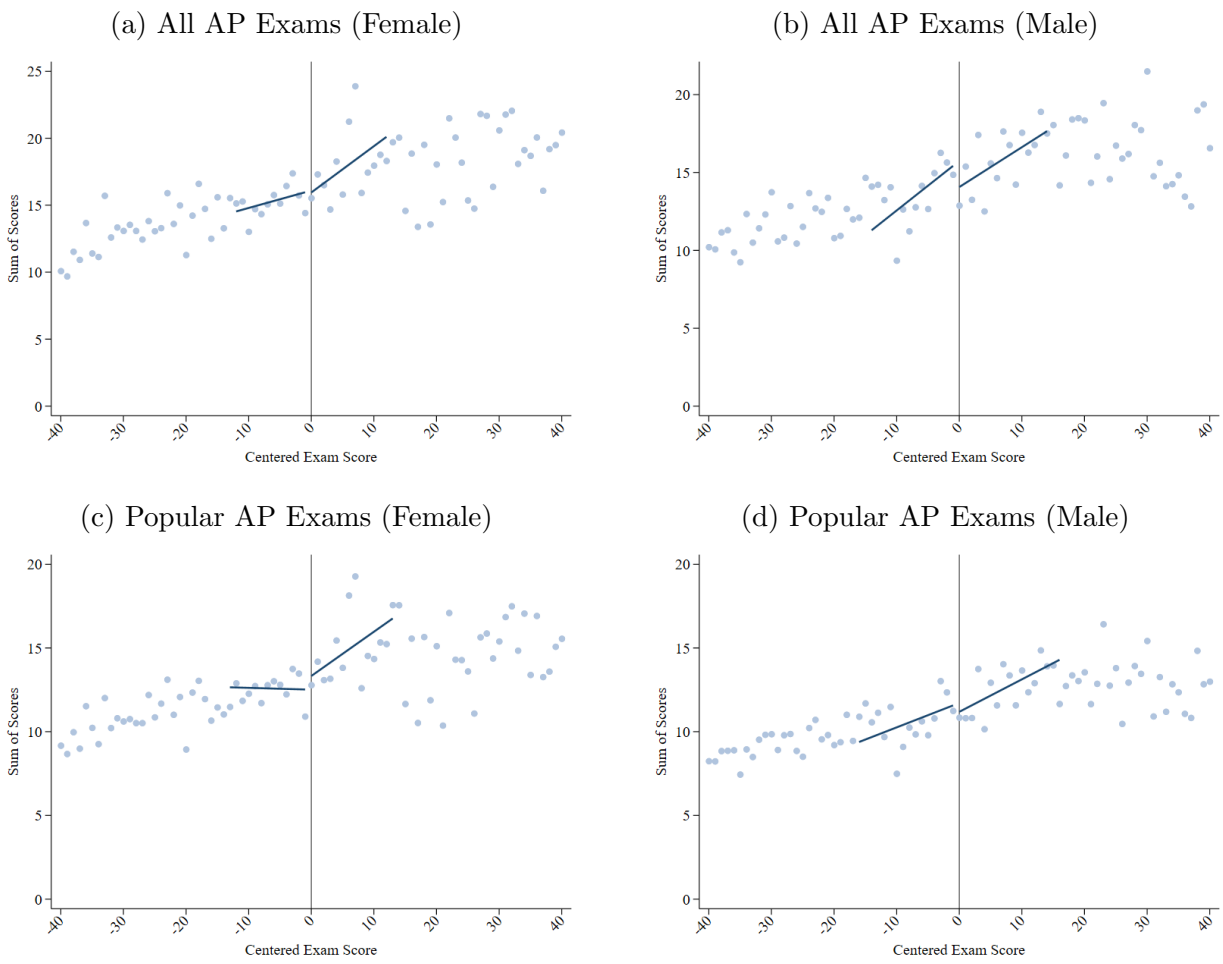


Figure A5: AP Exam Heterogeneity by Sex

Notes: This figure illustrates the effect of being eligible for any Discovery Program on AP exam scores. Panels a and c on the left show the effect on AP exam scores for female students and Panels b and d on the right show the effect for male students. The top two panels report results for the sum of scores over all AP exams and the bottom panels report the results for the sum of scores over popular AP exams. Each panel plots average AP sum of scores in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

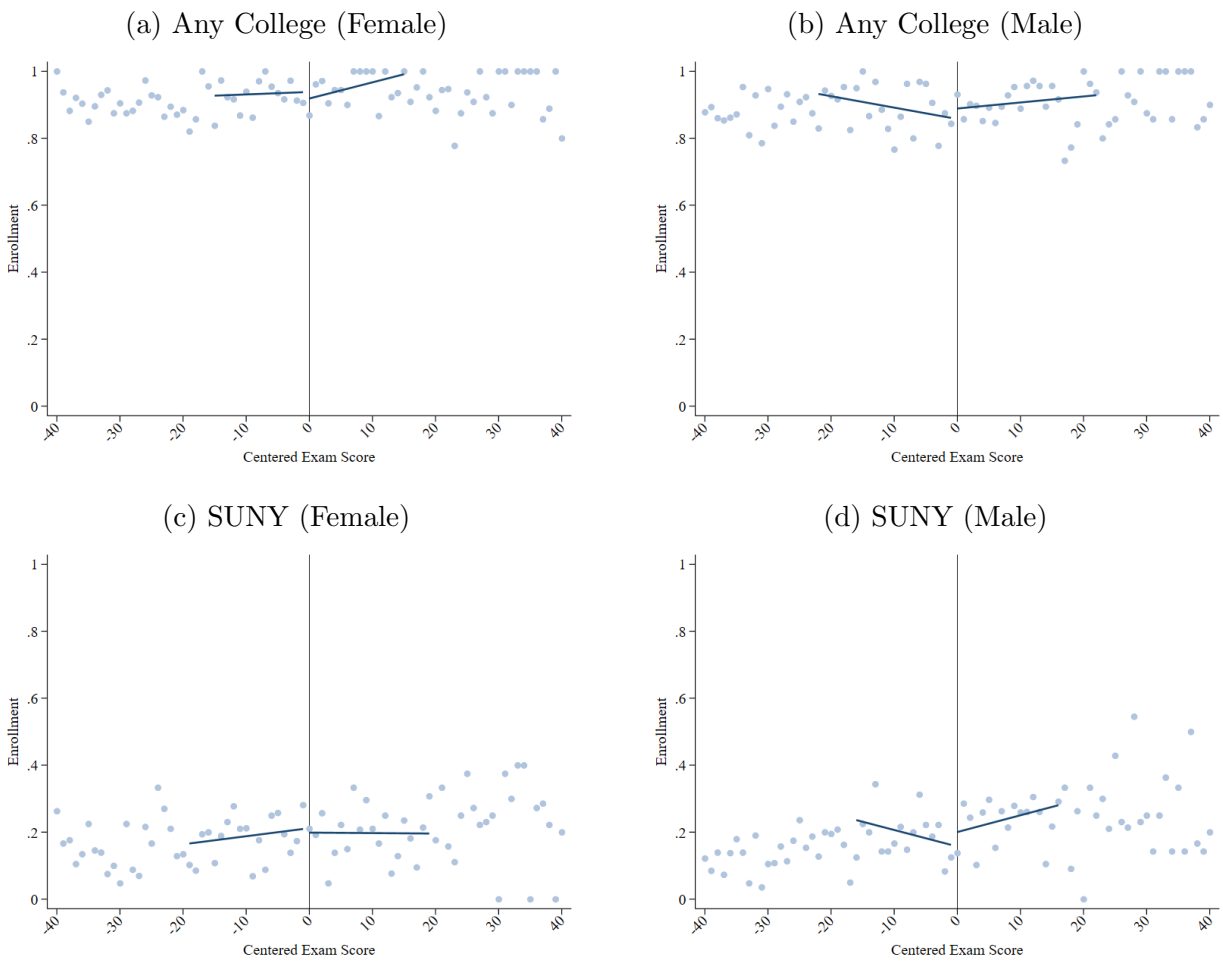


Figure A6: College Enrollment Heterogeneity by Sex

Notes: This figure illustrates the effect of being eligible for any Discovery Program on college enrollment. Panels a and c on the left show the effect on college enrollment for female students and Panels b and d on the right show the effect for male students. The top two panels report enrollment in any college and the bottom panels report enrollment in the SUNY system. Each panel plots average enrollment in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

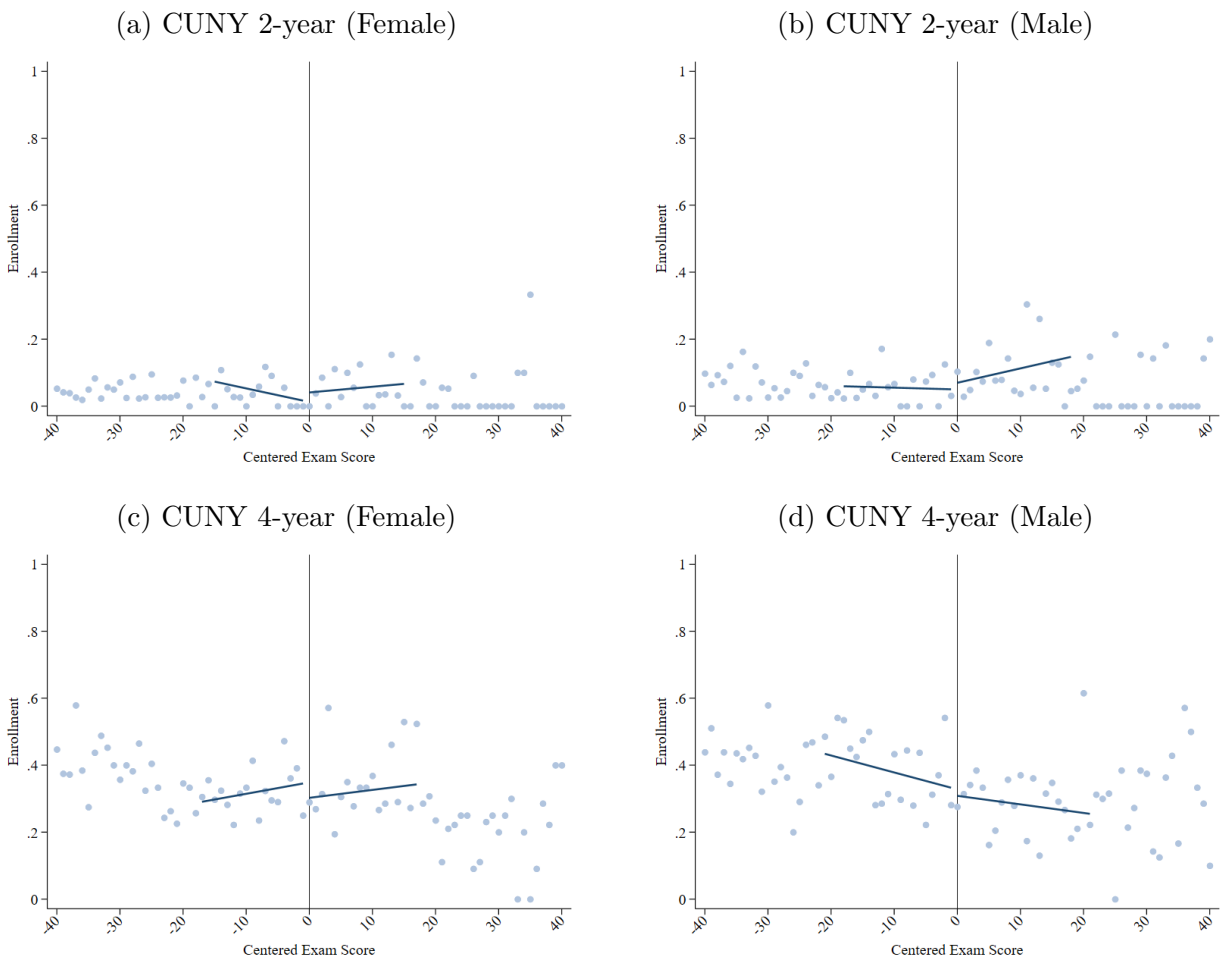


Figure A7: CUNY Enrollment Heterogeneity by Sex

Notes: This figure illustrates the effect of being eligible for any Discovery Program on CUNY enrollment. Panels a and c on the left show the effect on CUNY enrollment for female students and Panels b and d on the right show the effect for male students. The top two panels report enrollment in a 2-year CUNY program and the bottom panels report enrollment in a 4-year CUNY program. Each panel plots average enrollment in one-point centered SHSAT bins. The superimposed solid lines are based on local linear fits of the underlying unbinned data.

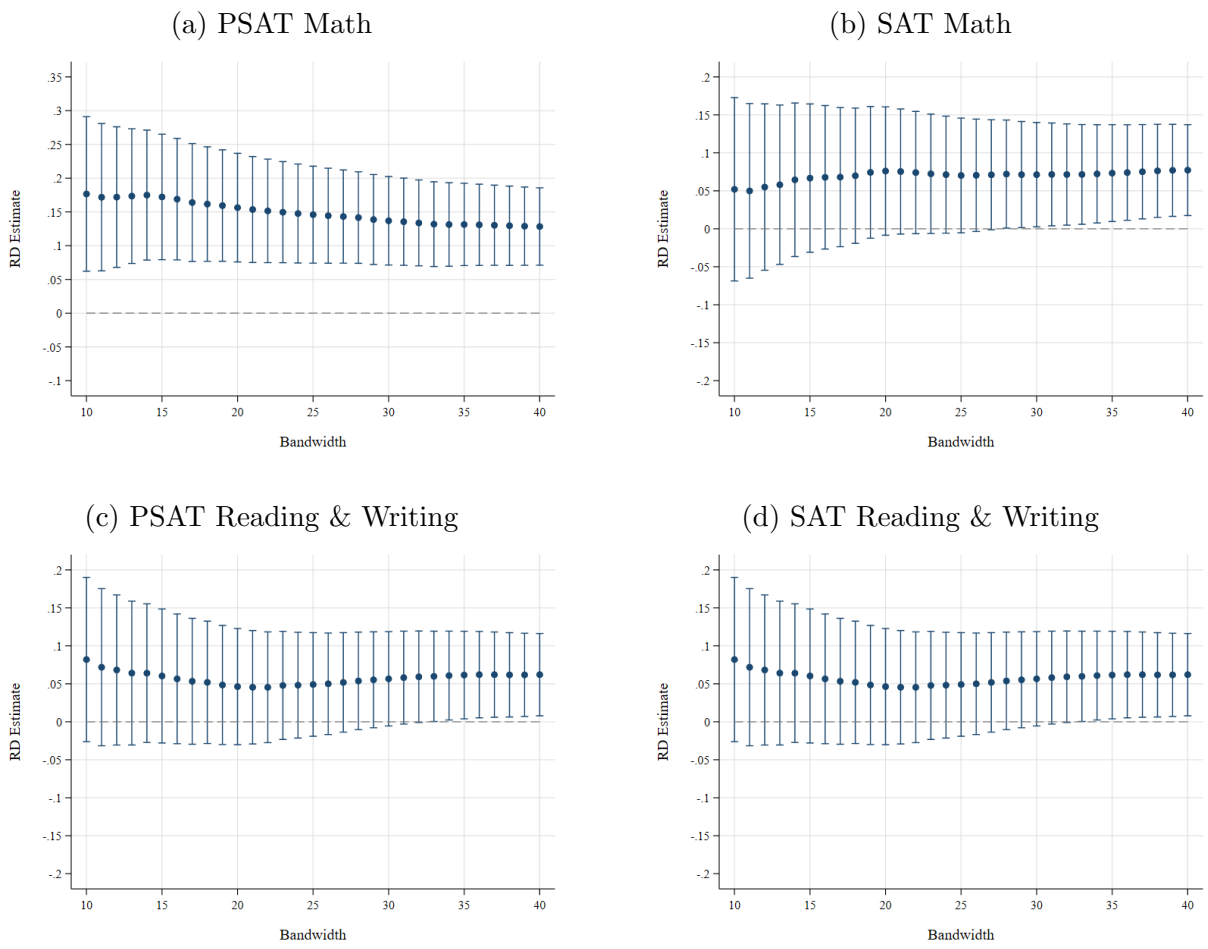


Figure A8: Bandwidth Sensitivity I

Notes: This figure plots reduced form (ITT) estimates with alternative bandwidths. Each estimate and 95% confidence interval comes from a local linear RD regression using an alternative bandwidth. For each value on the x-axis, I re-estimate equation 1 using a bandwidth of (-X,X).

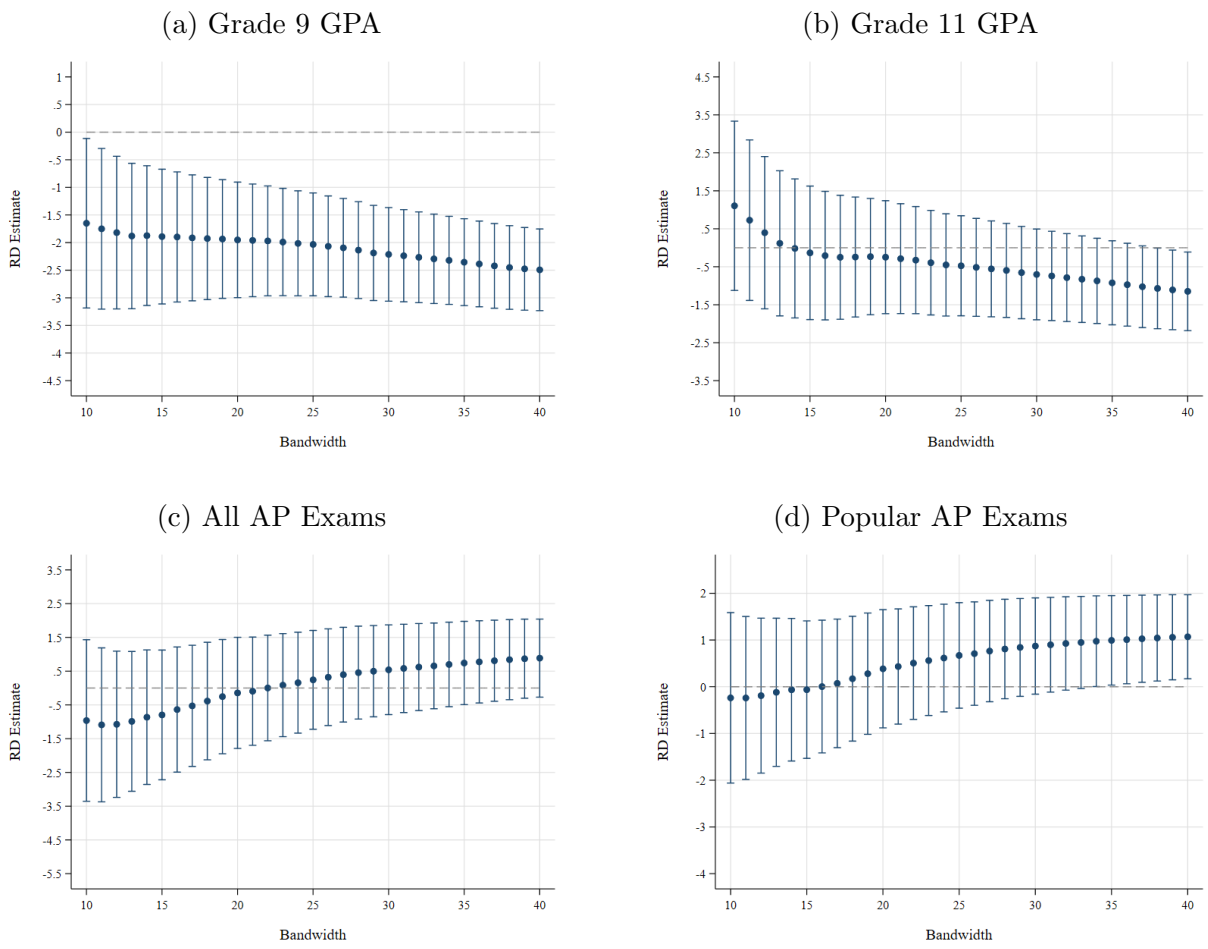


Figure A9: Bandwidth Sensitivity II

Notes: This figure plots reduced form (ITT) estimates with alternative bandwidths. Each estimate and 95% confidence interval comes from a local linear RD regression using an alternative bandwidth. For each value on the x-axis, I re-estimate equation 1 using a bandwidth of (-X,X).

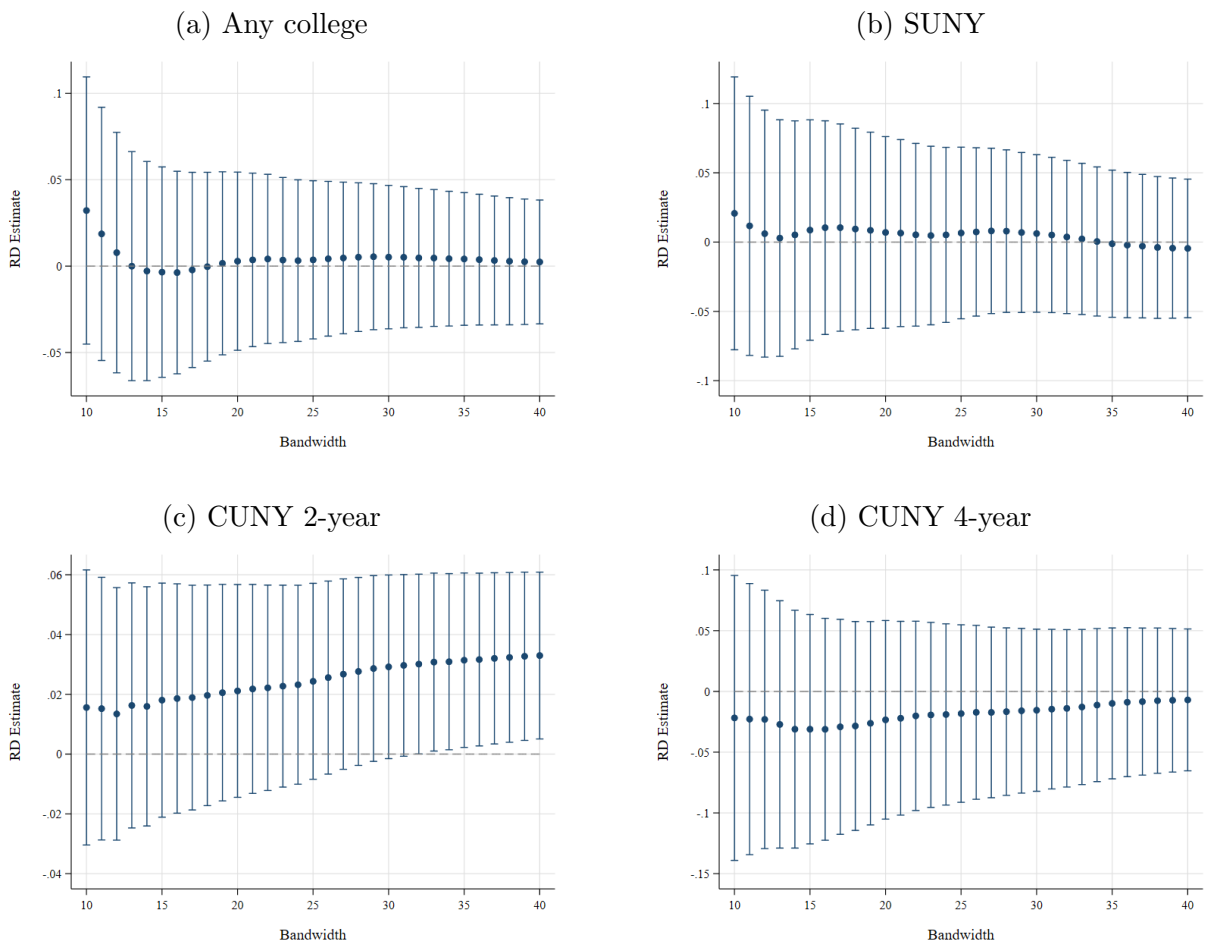


Figure A10: Bandwidth Sensitivity III

Notes: This figure plots reduced form (ITT) estimates with alternative bandwidths. Each estimate and 95% confidence interval comes from a local linear RD regression using an alternative bandwidth. For each value on the x-axis, I re-estimate equation 1 using a bandwidth of (-X,X).

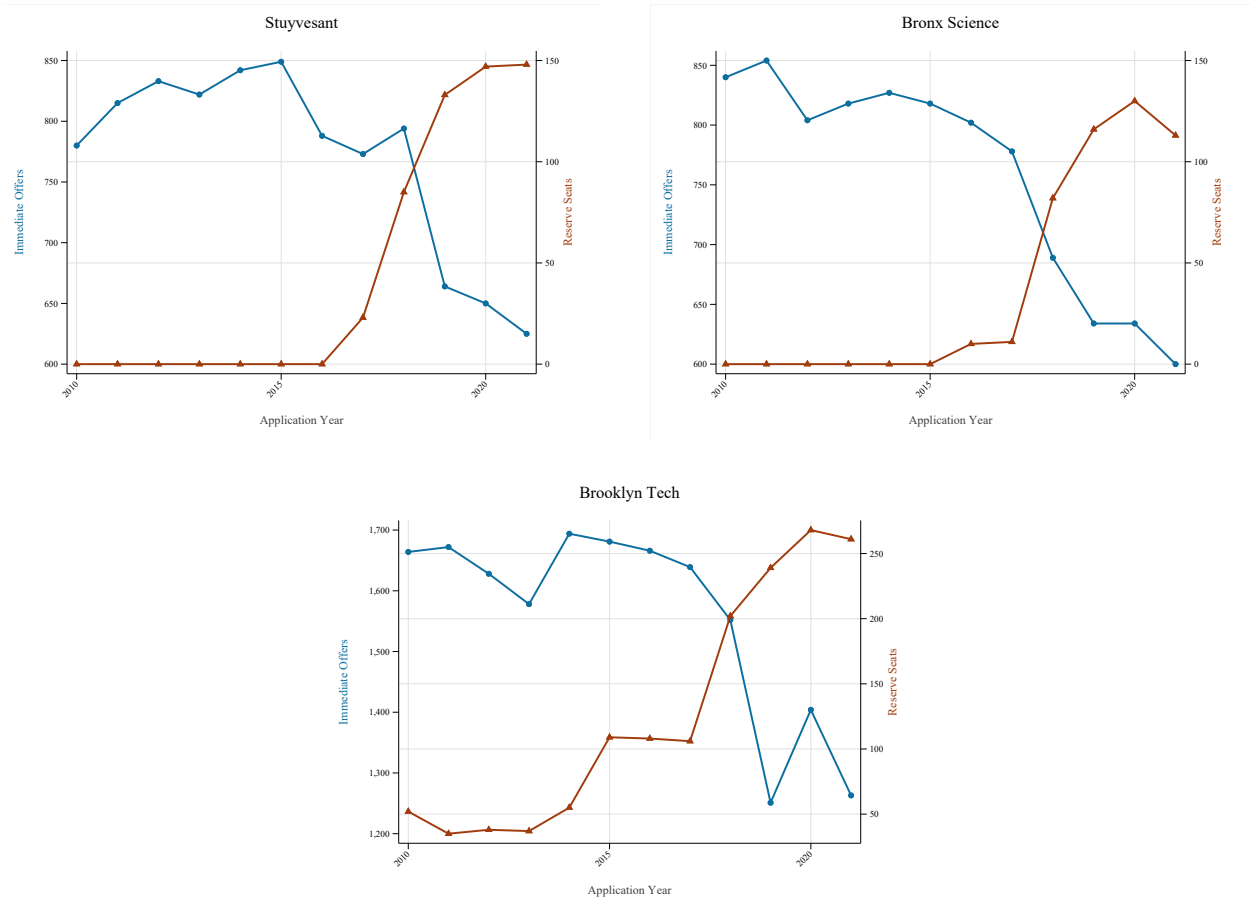


Figure A11: "Big 3" Enrollment Trends by Seat Type

Notes: This figure plots enrollment trends at the "Big 3" Specialized High Schools by application year. The left y-axis plots the number of immediate (non-reserve) offers made in each application year. The right y-axis plots the number of students that attend the school's Discovery Program for each application cohort. Data on Summer program attendance for Brooklyn Tech in 2021 is missing. I use ninth grade enrollment of students who fail to receive an immediate offer, but still enroll the next year as a lower bound on Summer program attendance.

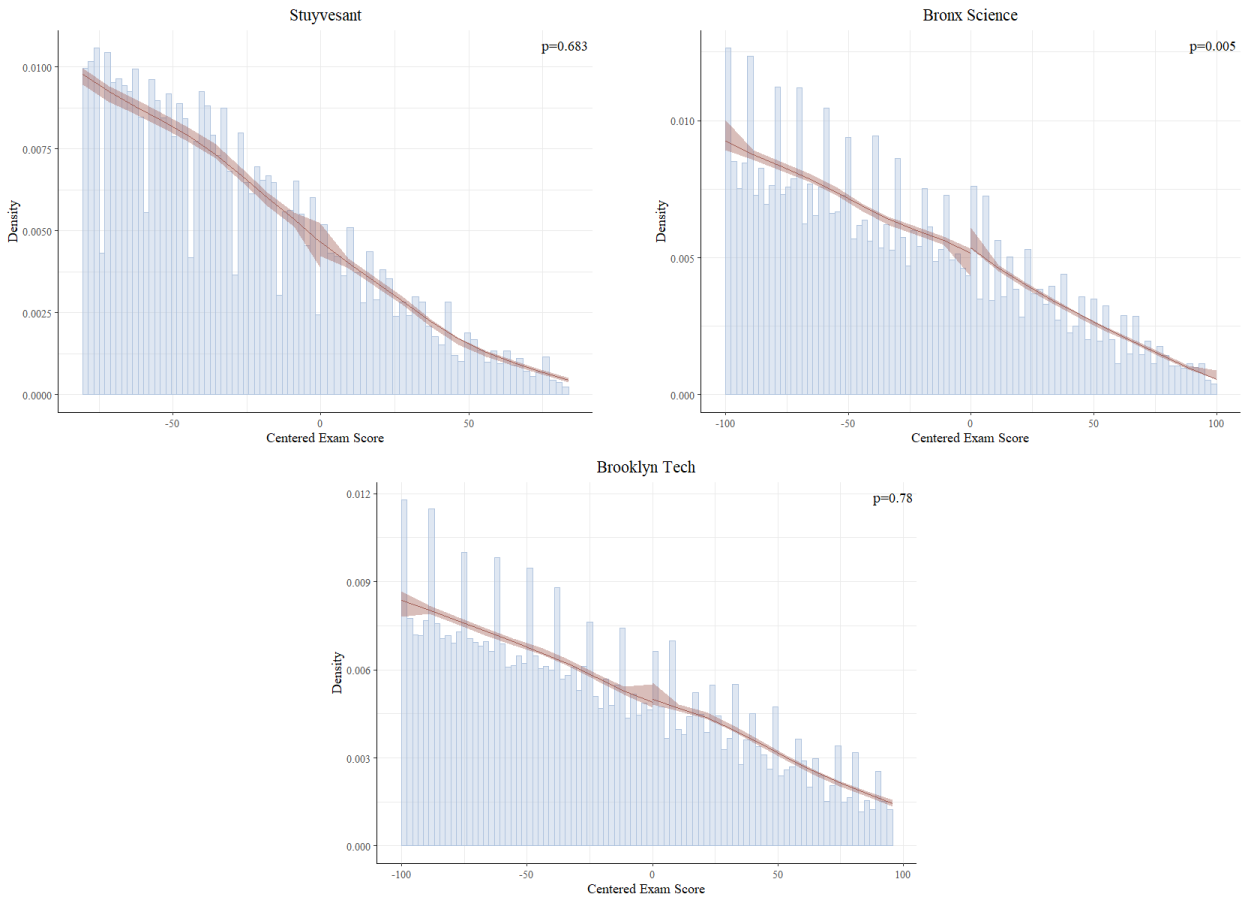


Figure A12: "Big 3" Running Variable Density Tests

Notes: This figure shows density tests around the cutoff of each "Big 3" school following Cattaneo et al. (2018). Each plot reports the p-value of no manipulation around each particular cutoff.

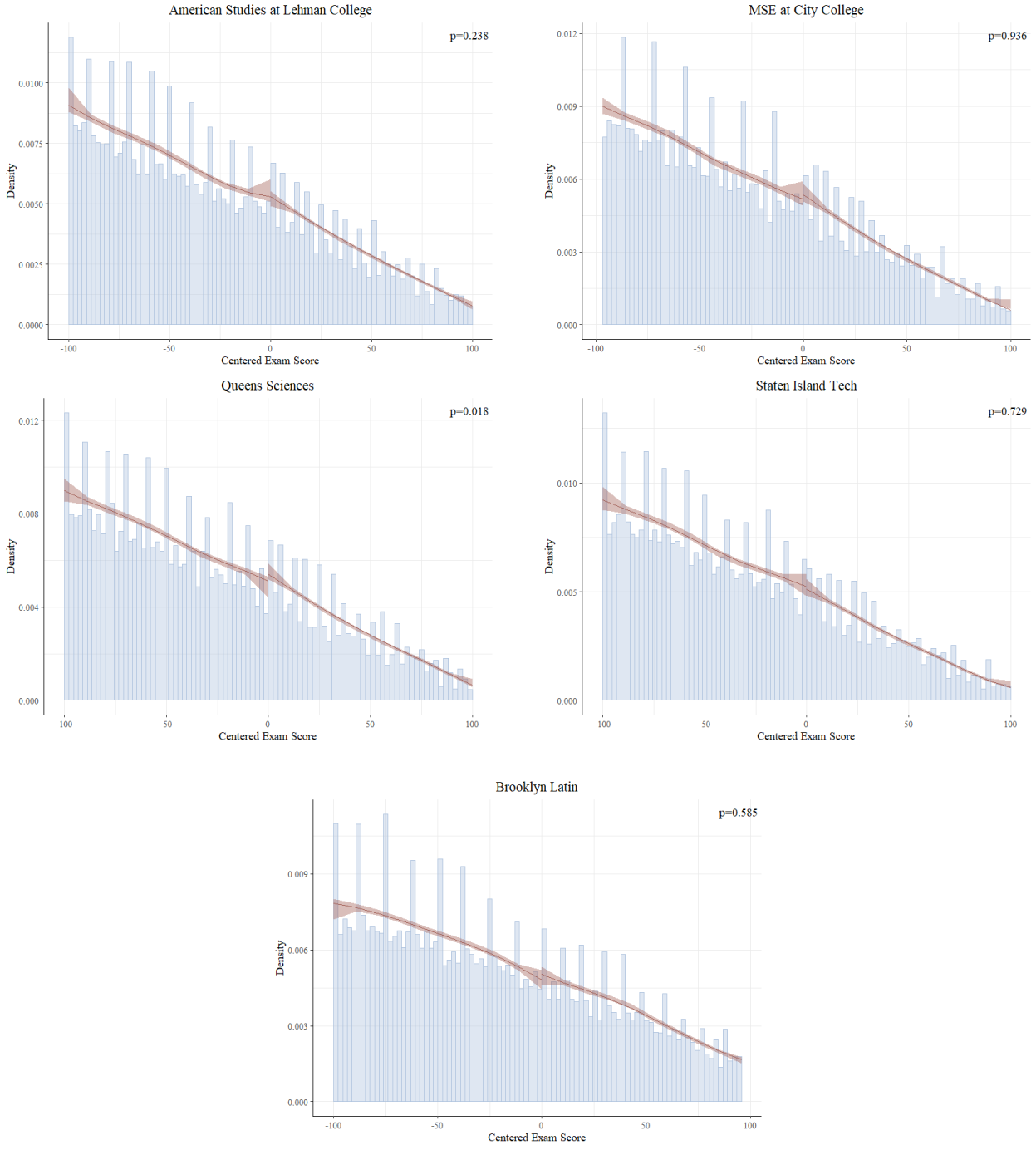


Figure A13: Exam School Running Variable Density Tests

Notes: This figure shows density tests around the cutoff of each of the five additional exam schools following Cattaneo et al. (2018). Each plot reports the p-value of no manipulation around each particular cutoff.

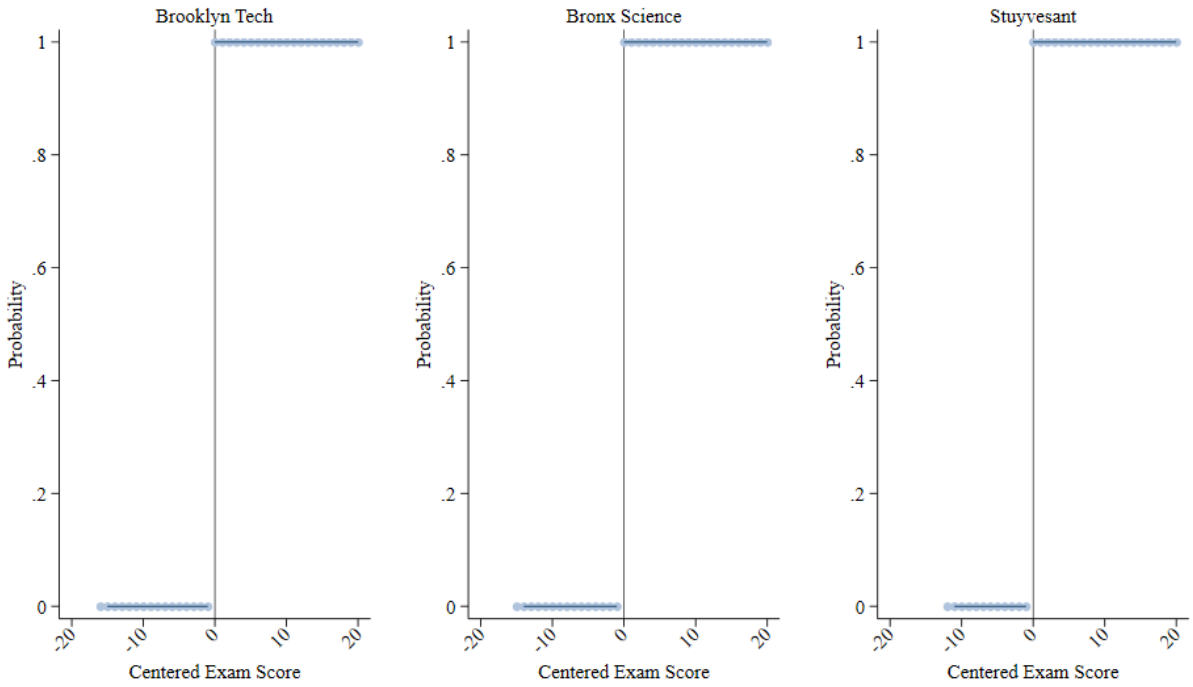
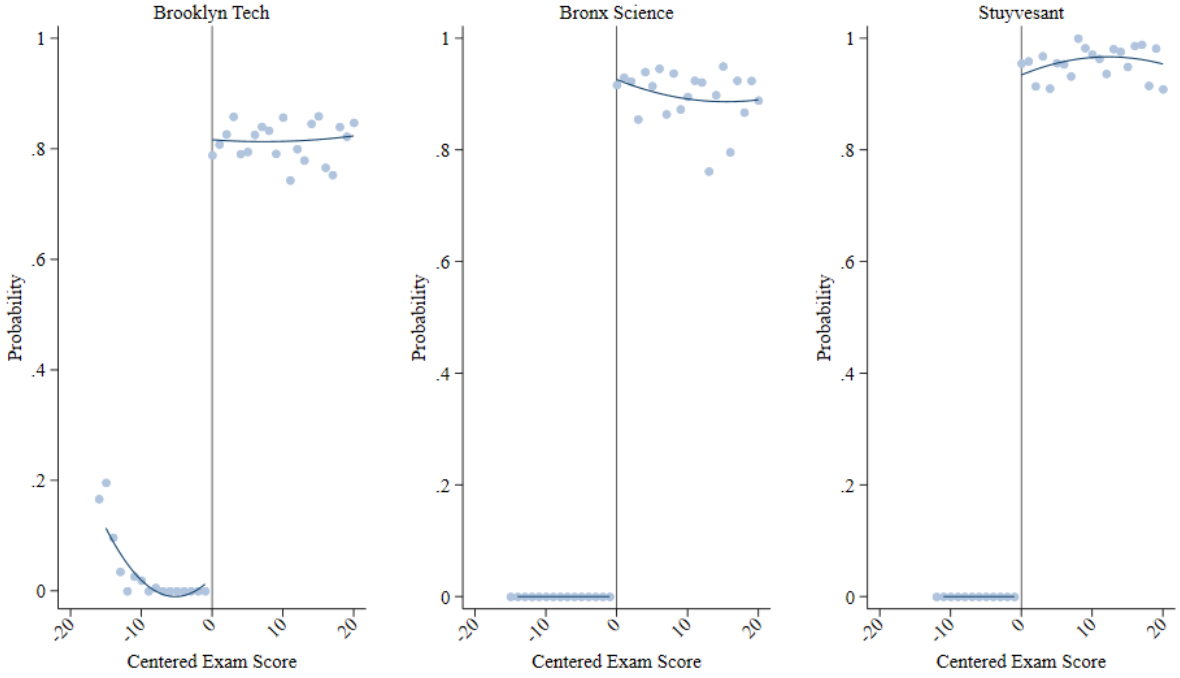


Figure A14: Specialized High School Offers in Displacement Samples

Notes: This figure plots the probability of receiving an offer to each of the "Big 3" Specialized High School by one-point centered SHSAT bins. The analysis sample for each school is restricted to applicants who would receive an offer to that school under the counterfactual assignment match.

(a) Enrollment at each Specialized High School



(b) Enrollment at any Specialized High School

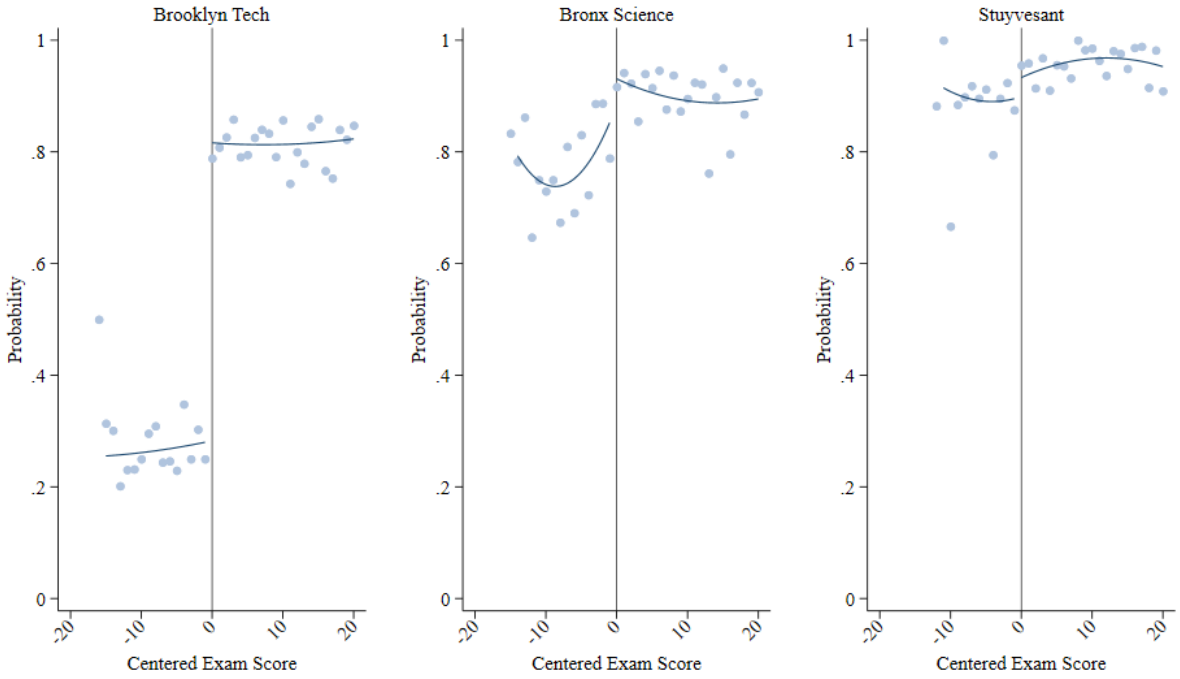


Figure A15: Specialized High School Enrollment in Displacement Samples

Notes: This figure plots the probability of enrolling in each of the "Big 3" Specialized High School (a) and the probability of enrolling in any Specialized High School (b) by one-point centered SHSAT bins. The analysis sample for each school is restricted to applicants who would receive an offer to that school under the counterfactual assignment match.

Table A1: Exam School Cutoffs by Seat Type and Application Year

	Stuyvesant		Bronx Sci		Brooklyn Tech		MSE		Lehman		SI Tech		Queens Sci		Brooklyn Latin	
	Reserve	Regular	Reserve	Regular	Reserve	Regular	Reserve	Regular	Reserve	Regular	Reserve	Regular	Reserve	Regular	Reserve	Regular
2010	.	566	.	515	468	486	468	498	.	508	.	498	467	508	462	472
2011	.	560	.	512	469	482	469	492	.	502	.	496	468	508	465	472
2012	.	561	.	513	468	484	469	497	.	501	.	505	469	512	465	471
2013	.	559	.	517	476	486	477	504	.	506	474	506	475	511	475	479
2014	.	556	.	510	472	482	472	499	.	503	466	508	472	504	468	477
2015	.	552	.	511	467	482	465	500	470	506	463	507	469	504	463	476
2016	.	555	477	511	469	486	473	500	474	505	470	515	475	503	467	479
2017	479	559	479	518	472	493	472	516	475	516	472	519	472	511	469	482
2018	471	557	463	524	461	497	468	519	463	518	459	526	468	514	458	486
2019	466	566	455	531	454	507	461	522	456	517	452	529	463	522	450	494
2020	452	559	440	517	437	493	449	515	438	502	438	520	455	515	432	481
2021	465	563	455	524	452	506	462	532	455	516	450	527	465	523	447	497

Notes: This table presents SHSAT score cutoffs for each school in each application year, by seat type. Reserve seat (Discovery) cutoffs are provided directly in the NYCDOE administrative data. Regular cutoffs are calculated by the author as the lowest score among students accepted to each school by application year.

Table A2: RD Estimates for Control Variables as Outcomes

	Estimate (1)	Mean (2)	N (3)
Asian	0.042	0.56	4,216
	(0.032)		
Black	-0.017	0.10	4,216
	(0.020)		
Hispanic	-0.019	0.22	4,216
	(0.027)		
White	-0.001	0.11	4,868
	(0.020)		
Female	-0.064*	0.53	3,786
	(0.036)		
SWD	0.011	0.02	4,011
	(0.008)		
Residence in Brooklyn	0.030	0.39	4,864
	(0.029)		
Residence in Bronx	-0.037	0.16	3,783
	(0.024)		
Residence in Manhattan	0.003	0.06	4,418
	(0.015)		
Residence in Queens	-0.018	0.35	5,092
	(0.028)		
Residence in Staten Island	0.014	0.03	3,129
	(0.013)		

Notes: This table reports reduced form (ITT) estimates on (pre-determined) covariates. The estimates come from estimating Equation 1 with covariates as outcomes and triangular weights. Covariate-specific bandwidths are estimated using the same mean square error-optimal procedure as the achievement outcomes. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A3: Estimates with Uniform Kernel

	PSAT		SAT		GPA		AP exams		College enrollment			
	Math	Reading	Math	Reading	Grade 9	Grade 11	All exams	Popular exams	Any college	CUNY 2-year	CUNY 4-year	SUNY
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: First Stage												
Enrollment	0.540***	0.557***	0.571***	0.559***	0.537***	0.550***	0.513***	0.499***	0.554***	0.561***	0.548***	0.540***
	(0.021)	(0.020)	(0.022)	(0.023)	(0.023)	(0.023)	(0.026)	(0.028)	(0.027)	(0.026)	(0.027)	(0.028)
N	3,786	4,216	3,873	3,517	3,350	3,359	2,503	2,129	2,493	2,597	2,374	2,249
Panel B: Reduced Form (ITT)												
Any offer	0.139***	0.031	0.067*	0.052	-1.950***	-0.151	-0.386	0.040	0.015	0.026	-0.029	0.014
	(0.041)	(0.037)	(0.038)	(0.036)	(0.575)	(0.710)	(0.963)	(0.796)	(0.025)	(0.018)	(0.041)	(0.036)
N	3,049	3,406	3,417	3,104	3,146	3,075	1,950	1,633	2,256	2,351	2,142	2,030
Panel C: 2SLS (LATE)												
Any Offer	0.237***	0.052	0.114*	0.089	-3.509***	-0.266	-0.847	0.093	0.026	0.046	-0.051	0.025
	(0.069)	(0.061)	(0.064)	(0.062)	(1.023)	(1.242)	(2.097)	(1.821)	(0.043)	(0.031)	(0.072)	(0.064)
N	3,049	3,406	3,417	3,104	3,146	3,075	1,950	1,633	2,256	2,351	2,142	2,030

Notes: This table reports first stage, reduced form, and 2SLS estimates using a uniform kernel. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A4: Reduced Form Estimates from Alternative Specifications

	LLR (1)	LLR (2)	LLR (3)	LLR (4)	LLR with covariates (5)	Quadratic (6)	Global quartic (7)
Panel A: Achievement outcomes							
PSAT Math	0.139***	0.155***	0.141***	0.165***	0.144***	0.189***	0.184***
	(0.046)	(0.045)	(0.046)	(0.045)	(0.043)	(0.065)	(0.058)
PSAT Reading	0.046	0.056	0.041	0.051	0.058	0.089	0.073
	(0.042)	(0.040)	(0.042)	(0.041)	(0.041)	(0.059)	(0.053)
SAT Math	0.082*	0.075*	0.089**	0.075*	0.044	0.058	0.067
	(0.043)	(0.042)	(0.043)	(0.042)	(0.040)	(0.061)	(0.054)
SAT Reading	0.042	0.037	0.040	0.037	0.037	0.005	0.019
	(0.040)	(0.039)	(0.040)	(0.040)	(0.039)	(0.060)	(0.051)
Grade 9 GPA	-1.932***	-1.930***	-1.928***	-1.885***	-1.889***	-1.597*	-1.861**
	(0.626)	(0.625)	(0.627)	(0.629)	(0.605)	(0.966)	(0.821)
Grade 11 GPA	-0.297	-0.342	-0.262	-0.240	-0.356	0.733	0.349
	(0.804)	(0.796)	(0.804)	(0.799)	(0.790)	(1.229)	(1.038)
All AP exams	-0.965	-0.828	-1.024	-0.922	-1.295	-0.755	-1.254
	(1.032)	(1.034)	(1.024)	(1.034)	(1.005)	(1.561)	(1.330)
Popular AP exams	-0.290	-0.165	-0.343	-0.195	-0.515	0.275	-0.388
	(0.842)	(0.844)	(0.843)	(0.850)	(0.829)	(1.259)	(1.084)
Panel B: Postsecondary enrollment outcomes							
Any college	0.001	0.001	0.000	0.001	-0.001	0.009	-0.006
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.042)	(0.036)
CUNY 2-year	0.025	0.025	0.021	0.021	0.017	0.013	0.009
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.025)	(0.023)
CUNY 4-year	-0.041	-0.041	-0.033	-0.029	-0.036	-0.025	-0.024
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.066)	(0.057)
SUNY	0.013	0.012	0.015	0.010	0.007	0.015	0.002
	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)	(0.058)	(0.051)
Application cohort FE		X					
Qualifying cutoff FE			X				
Qualifying cutoff × application cohort FE				X	X	X	X

Notes: This table reports reduced form (ITT) estimates using alternative specifications. Column 1 reports estimates using local linear controls of the running variable and no fixed effects. Columns 2 and 3 report estimates using a local linear function of the running variable controls, in addition to application cohort fixed effects and qualifying cutoff fixed effects, respectively. Column 4 reports the main estimates presented in Table 2, which use a local linear function of the running variable controls. Column 5 reports estimates of Equation 1 with the addition of several covariates including indicators for whether a student is female, black, hispanic, or asian. Indicators for each neighborhood of residence (using Manhattan as the reference category) are included as well. Column 6 reports estimates using a quadratic relationship between the running variable and each outcome. Column 7 reports estimates using the global quartic function specified in Equation 5. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A5: Sensitivity to Choice of PSAT and SAT Score

	PSAT		SAT	
	Math	Reading	Math	Reading
	(1)	(2)	(3)	(4)
Panel A: Score from maximum total				
Any offer	0.165***	0.051	0.075*	0.037
	(0.045)	(0.041)	(0.042)	(0.040)
N	3,049	3,406	3,417	3,104
Panel B: Superscore				
Any offer	0.173***	0.058	0.080*	0.049
	(0.045)	(0.040)	(0.042)	(0.039)
N	3,049	3,406	3,417	3,273
Panel C: First attempt				
Any offer	0.098**	-0.019	0.056	0.012
	(0.039)	(0.041)	(0.039)	(0.038)
N	3,568	3,049	3,417	3,104

Notes: This table presents estimates of Equation 1 using alternative choices of PSAT and SAT scores. Panel A reports estimates using the preferred outcome shown in Table 2, this is the section score associated with a student's highest total standardized test score. Panel B reports estimates using each student's "superscore," the highest section score across all attempts. Panel C reports estimates using each student's first attempt on the respective standardized test. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A6: Pushed Out RD Estimates for Control Variables as Outcomes

	Stuyvesant			Bronx Science			Brooklyn Tech		
	Estimate (1)	Mean (2)	N (3)	Estimate (4)	Mean (5)	N (6)	Estimate (7)	Mean (8)	N (9)
Asian	-0.015	0.722	1,272	0.056	0.675	1,716	-0.020	0.589	4,572
	(0.052)			(0.046)			(0.029)		
Black	-0.001	0.010	1,272	0.021	0.011	1,716	0.000	0.037	4,572
	(0.008)			(0.017)			(0.012)		
Hispanic	0.023	0.038	1,272	-0.003	0.070	1,716	-0.014	0.061	4,572
	(0.026)			(0.024)			(0.015)		
White	0.020	0.170	1,272	-0.045	0.197	1,716	0.027	0.277	4,572
	(0.044)			(0.037)			(0.027)		
Female	0.087	0.424	1,272	-0.016	0.489	1,716	0.051*	0.459	4,572
	(0.060)			(0.051)			(0.030)		
SWD	-0.024	0.020	1,272	-0.003	0.015	1,716	-0.009	0.020	4,572
	(0.015)			(0.013)			(0.009)		
Residence in Brooklyn	0.049	0.332	1,269	-0.018	0.022	1,709	0.051*	0.433	4,564
	(0.056)			(0.016)			(0.029)		
Residence in Bronx	-0.005	0.013	1,269	0.008	0.111	1,709	-0.005	0.029	4,564
	(0.015)			(0.031)			(0.012)		
Residence in Manhattan	-0.019	0.213	1,269	0.008	0.229	1,709	-0.013	0.172	4,564
	(0.050)			(0.041)			(0.022)		
Residence in Queens	-0.052	0.425	1,269	0.003	0.639	1,709	-0.004	0.320	4,564
	(0.059)			(0.048)			(0.029)		
Residence in Staten Island	0.028	0.017	1,269	-0.001	0.000	1,709	-0.028**	0.045	4,564
	(0.018)			(0.001)			(0.012)		

Notes: This table reports reduced form (ITT) estimates on (pre-determined) covariates. The estimates come from estimating Equation 6 with covariates as outcomes and triangular weights. Columns (2), (5), and (8) report mean covariates for applicants to the right of the cutoff. Robust standard errors are reported in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

B Data Appendix

Enrollment Data

Annual (collected in June) enrollment files provide records of biographical information as well as each student's grade level and the code for the public school they enroll at in that academic year.[41] The demographic information includes student's birth month & year, gender, ethnicity, home language, English Language Learner status, whether they have an Individualized Education Program (IEP), and whether they are eligible for free or reduced price lunch (FRPL) or have been identified by the Human Resources Administration as receiving certain types of public assistance. Files are organized by eighth grade cohort. Each cohort contains five enrollment files: one for each academic year from eighth grade (high school application year) to on-time graduation. I append all files to create an enrollment panel. A small number of students appear in more than one eighth grade cohort, I drop these students from the analysis. This enrollment file is used as the master file. I merge the enrollment panel with an attendance panel before reshaping the dataset to be one observation per applicant, with columns organized by academic years from application year. Next, I merge this with all other files by an unique student identifier.

Attendance Data

I construct an attendance panel in the same way that I construct the enrollment panel. This includes the total number of days absent and present for each student. Once the full panel is constructed, I merge it with the enrollment panel. I drop any observations that are found only in the attendance file (and not in the enrollment file). This combined enrollment and attendance panel is then reshaped to contain one observation per student.

SHSAT & Discovery Data

The NYCDOE SHSAT & Discovery dataset contains a record for each student who takes the SHSAT in eighth grade. For eighth grade students interested in attending an exam school, the SHSAT is typically offered in late October. Students in ninth grade also have the option to take a slightly different version of the test in November (or early December). The SHSAT is a multiple-choice exam with sections in verbal and math that students must complete in a 2 hour and 30 minute time period. Raw test scores are scaled for both sections based on the number of questions a student answers correctly and the difficulty level of those questions. The scale scores for each section are then combined into a composite score with a maximum of 700 points. The test is free to take and eighth grade students attending a NYCPS take the exam at their current school. Records in this file include each student's SHSAT scaled score, rank-ordered list of specialized high school preferences, acceptance and eligibility status at each school, indicators for Discovery Program invitation and attendance, and the school code of the specialized high school a student is invited to attend (if invited). The data pertaining to the Discovery Program is hand-collected by the NYCDOE. The files

[41] Charter school students are not included in these files.

also includes cutoff scores for each school. First, I append files across cohorts to create a single SHSAT & Discovery dataset. Next, I merge this onto the wide enrollment/attendance file. For the main analysis, only exam school applicants are required. Thus, all students who do not take the SHSAT are dropped.

SAT Data

All SAT data were provided by NYCPS. I append all SAT files within and across eighth grade cohorts. As is common in the literature, if a student took the SAT more than once, I use the highest total score across all test attempts. Using all SAT takers in NYCPS, I standardize test scores by eighth grade cohort and test subject. I then merge the full SAT file with the wide enrollment file. For any analysis of cohorts that took the SAT prior to 2016 I account for the 2016 redesign of the SAT by converting pre-redesign scores using the official concordance tables from the College Board.[42]

PSAT Data

As with the SAT data, all PSAT data were provided by NYCPS. If a student took the PSAT more than once, I use the highest total score across all test attempts. These files are organized in the same manner as the enrollment files. I exclude the file that corresponds to twelfth grade for students graduating on-time (in four years) and append the rest of the files across years and cohorts. Using all SAT takers in NYCPS, I standardize test scores by eighth grade cohort and test subject. I then merge the full PSAT file with the wide enrollment file. The PSAT was also redesign in 2016, I account for the redesign by converting pre-redesign PSAT scores using the official concordance tables from the College Board.[43]

AP Data

Advanced Placement (AP) data was provided by the NYCDOE. There is a record for each exam a student takes (i.e. there are multiple records for a student who takes more than one AP exam). AP tests are not required of NYC students and are administered at the end of the school year for students who have attended the corresponding AP course. Students that did not take any AP exams were assigned zeros on all AP-related outcome variables.

Credits and GPA Data

Data on credits and GPA contain the number of credits attempted and earned in each subject and total GPA as well as GPA in each subject (GPA data for students applying in 2010-11 and 2011-12 is not available). I append all files within and across cohorts before reshaping to a wide file with one observation per student. The GPA/credits file is then merged with the wide enrollment file. GPA is reported on a 100-point scale, but values may exceed 100 percent due to weighting of advanced courses. Schools cannot give more credit for advanced courses, but they may give more weight to those courses when calculating GPA. I present estimates of GPA using the original 100-point GPA scale. In the body of the paper I make

[42] College Board Concordance Tables for SAT scores.
[43] College Board Concordance Tables for PSAT scores.

a quick translation to a 4.0 scale for comparison to other papers in the literature. This is done by simply dividing the coefficient by 25.

Postsecondary Enrollment Data

The postsecondary enrollment data are collected each year for the Fall of the academic year that a student would enter college if they did so immediately after on-time graduation. The dataset includes records of two or four-year college enrollment and the type of institution - CUNY, SUNY, private NY State, or out of state institution.