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

Michael Darisse†

March 24, 2026

PRELIMINARY DRAFT. Please do not cite or circulate.

Abstract

This paper studies the New York City Department of Education 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 three- to five- week summer program. Using a regression discontinuity design (RDD) 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.

*I am grateful to Carl Kitchens, Luke P. Rodgers, and Shawn Kantor for their continued advice and support, as well as Benjamin Cosman and Lianna Wright at the New York City Department of Education for graciously sharing data. I thank Walter Ecton, Erica Harbatkin, Matthew Lenard, seminar participants at Florida State University, New York City Independent Budget Office, and conference participants at the Southern Economic Association and Association for Education Policy and Finance for helpful comments and suggestions.

†Department of Economics, Florida State University (email: mdarisse@fsu.edu).

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

High-quality education can lead to significant gains in educational and career outcomes, yet access to such high-quality education is often inequitable (Rouse and Barrow, 2006; Barrow and Schanzenbach, 2012; Deming, 2022). Much prior work has been devoted to the inequities that exist in elite institutions of higher education and the affirmative action policies set up to address them. However, less is known about the inequality in access to prestigious high schools and the impact of affirmative action admission policies established to increase representation among disadvantaged students.

This paper studies the effect of an affirmative action policy implemented to increase access to some of New York City's most elite public high schools. Roughly two-thirds of New York City students who attend Harvard, Princeton, or Yale graduated from one of the city's original three public exam schools[1]—Stuyvesant, Bronx Science, and Brooklyn Tech (Dobbie and Fryer, 2014). These schools are considered some of the most elite high schools in the country. In addition to being a pipeline to the Ivy League, 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 (7 in Physics,[2] 1

[1] In NYC, these exam schools are also known as "specialized" schools and are public high schools run by the NYC Department of Education.

[2] https://www.bxscience.edu/apps/pages/index.jsp?uREC_ID=3733&type=d&pREC_ID=134193

in Chemistry, and 1 in Economics[3]).

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 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

[3] https://www.bxscience.edu/apps/news/show_news.jsp?REC_ID=875548&id=1

that reserve seat offers 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 16 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 test score gains are larger for female students, while the initial drop in GPA is strongest for male students.

This paper connects to two primary strands of literature. The first strand investigates the impact of school quality, with a focus on exam schools. Estimating the effect of school quality on educational outcomes is a difficult task due to the inherent selection bias in school choice districts. However, because exam school admissions are a discontinuous function of a student's exam score, they allow for the credible identification of school quality. The strong internal validity in such contexts has led to a number of papers studying the effects of exam schools in the United States and abroad.[4]

In countries where secondary school assignment is done by ranking all students by a single exam or a composite score based on previous academic performance, school quality is found to improve performance on future test scores (Jackson, 2010; Pop-Eleches and Urquiola, 2013).[5] In contrast, several studies using data from the large urban districts of Boston, Chicago, and New York City 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). Returning to exam schools in Boston and New York City, Rokkanen (2015) develops a latent factor-based approach to study inframarginal applicants, 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

[4] 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.

[5] Additional studies of exam schools outside the U.S. include Clark (2010); Ajayi (2014); Lucas and Mbiti (2014); Dustan et al. (2017); and Luflade and Zaiem (2024).

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 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.[6] 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 test a hypothesis which may explain such negative effects. Supplementing the Chicago Public Schools data with data from the high-performing Noble Network charter schools, the authors provide evidence that the 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 have otherwise been successful.[7] In contrast to Chicago's place-based SEHS admission policy, my setting features an affirmative action admission policy based on students' household socioeconomic status. The eligibility criteria for affirmative action policies in K-12 education markets may have consequences for which students participate and the academic outcomes of those 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.

The remainder of the paper is organized as follows. Section 2 provides institutional details

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

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

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 7 concludes.

2 The Discovery Program

The New York City Department of Education provides robust school choice options to it's students and their families. Students interested in attending a public high school in New York can take several pathways.[8] 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 submit a rank-ordered list (ROL) of up to twelve schools and schools have set criteria by which they rank applicants.[9] 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

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

[9]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

the sole criterion for admission (making them known as "exam schools").[10] 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 each of the eight schools (these preferences are distinct from the ROL of up to twelve traditional public schools described above).[11] Students don't necessarily need to rank every school, but over 70 percent of students who take the exam do so (Dobbie and Fryer, 2014).

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 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).

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

[11]Students may also apply in the Fall of ninth grade for admission the following year. However, the Discovery Program is for rising ninth-grade students.

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 [12] *(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*[13]
- *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*
- *the family earns less than or equal to the reduced-price lunch income threshold (based on household size)*[14]

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.[15]

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

[12] Economic Need Index (ENI) of at least 60%.

[13] As defined by the McKinney-Vento Act.

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

[15] 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

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.[16] 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.[17] At Stuyvesant, the top-ranked specialized high 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.

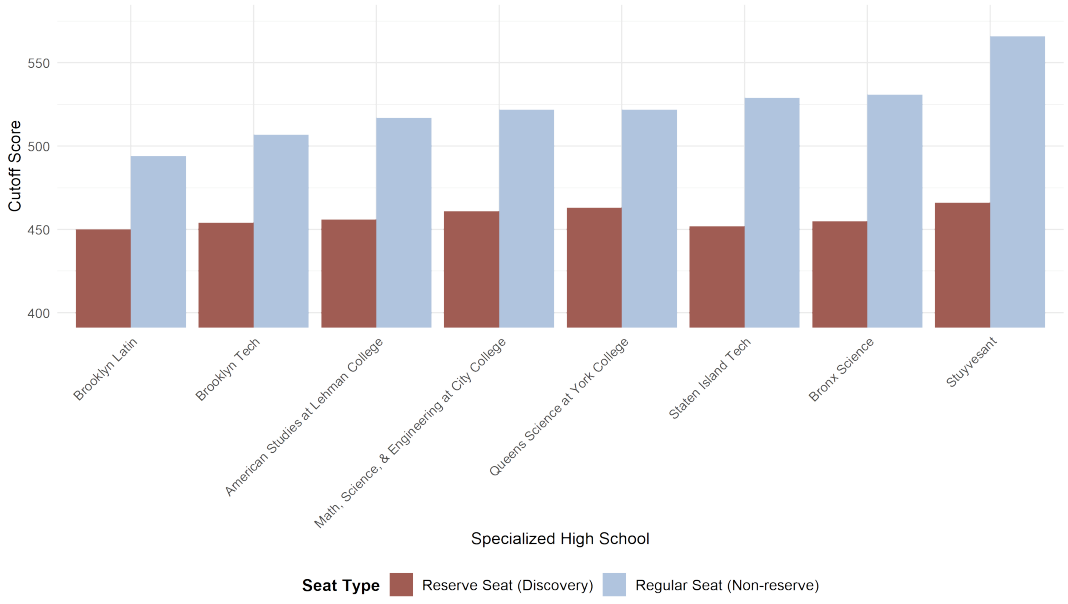


Figure 1: Specialized High School Admission Cutoffs by Seat Type

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

[16] Both letters are shown in the appendix.

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

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.[18] 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, 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, Advance Placement (AP) test scores, high school GPA, graduation status, and postsecondary enrollment.[19] 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,

[18]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 2000's, the program operated with a different process. Instead of students who scored below the cutoff for any specialized high school, Stuyvesant would admit disadvantage 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).

[19]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).

eligible, or not accepted at each school listed on their application.[20] These files also record each applicant's scaled score on the SHSAT.[21] 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 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.[22]

Student-level records are supplemented with school-level demographic data from the New York City Open Data Portal.[23] 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.

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

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

[22] Other scores are explored in Appendix Table A5.

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

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.

Table 1: Descriptive Statistics

	NYCPS 9th Graders by School Sector		Exam School Applicants		
	Exam Schools	Traditional Public Schools	All Applicants	Regular Offer	Discovery Attend
Asian	0.655	0.167	0.381	0.594	0.693
Black	0.028	0.232	0.156	0.025	0.063
Hispanic	0.062	0.436	0.235	0.057	0.151
White	0.219	0.141	0.199	0.282	0.078
Female	0.439	0.487	0.507	0.465	0.443
Free/reduced Price Lunch	0.544	0.778	0.642	0.443	0.954
English Language Learner	0.002	0.134	0.036	0.001	0.006
Student with Disability	0.016	0.236	0.063	0.020	0.012
N	17,579	287,000	106,419	18,871	2,474

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 (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 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. 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.

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, since the information given in the dataset does not perfectly correspond to the eligibility criteria, 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.[24]

[24]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

4 Empirical Strategy

To examine the achievement effects of attending an exam school through the reserve seat policy for 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, I draw on the "any-offer" design outlined in Abdulkadiroğlu et al. (2017) to estimate an overall exam school sector effect on disadvantaged students.[25] 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).[26] 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:

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

for consistency.

[25] I borrow notation from Angrist et al. (2023).

[26] 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 caution 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.

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.

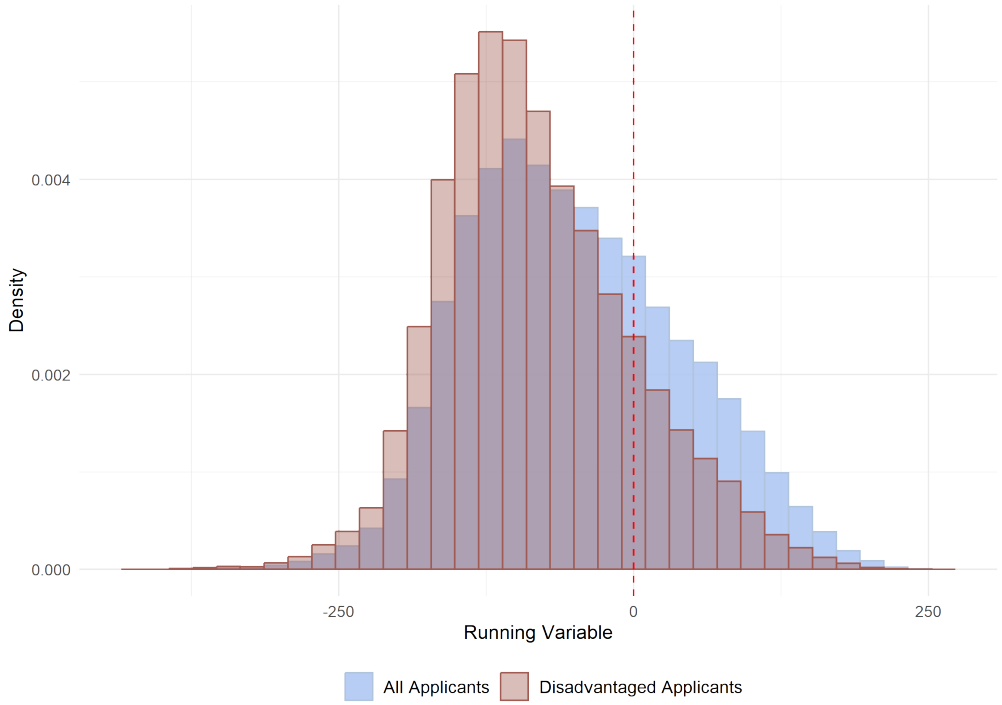


Figure 2: Distribution of centered SHSAT scores

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:

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

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,

$$h(r_{ic}) = \beta_1(r_{ic} - q^*_{ic}) + \beta_2 D_{ic} \times (r_{ic} - q^*_{ic}) \tag{2}$$

which is a piecewise local linear specification allowing the slope to change above and below the cutoff. The parameter of interest is δ, 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). This function takes the following form:

$$h(r_{ic}) = \sum_{p=0}^{4} \phi_p r_{ic}^p \tag{3}$$

and allows for polynomial coefficients that are fixed over the support of the running variable.

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.

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.[27] Figure 3 also shows that the probability of enrolling in an exam school increases to

[27]Specifically, the any-offer first stage for ninth grade exam school enrollment is 0.51. This estimate comes

approximately 75 percent as SHSAT scores rise. This likely reflects the fact that applicants with slightly higher SHSAT scores have more enticing offers and are more willing to accept them.

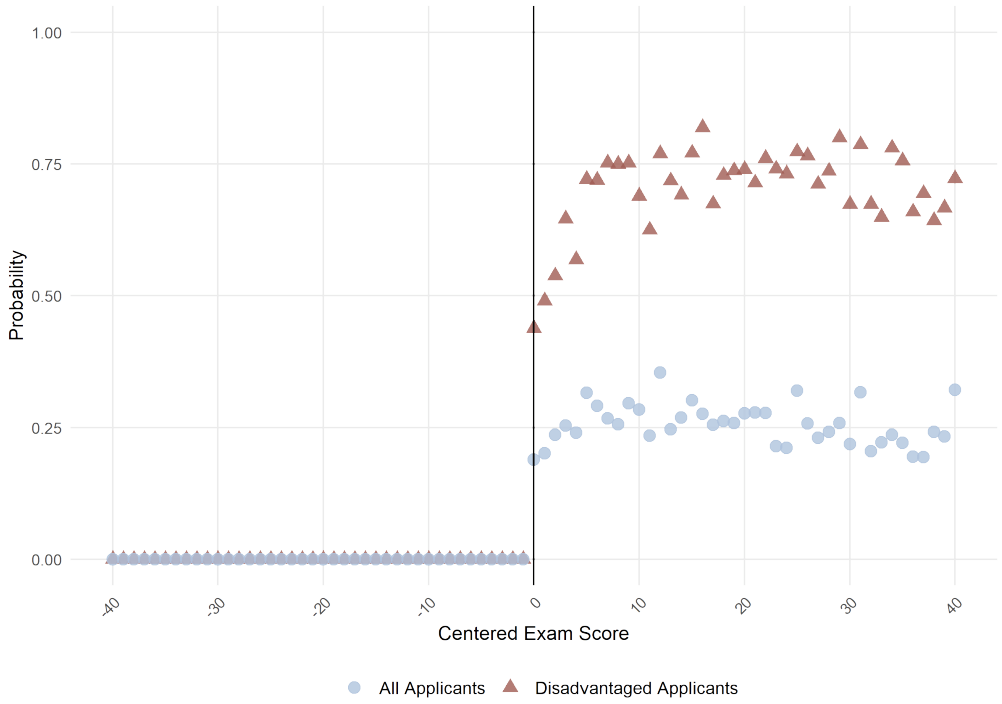


Figure 3: Probability of Enrolling in a Specialized High School

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.

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 two-stage least squares (2SLS) setup:

$$C_{ic} = \gamma_1 D_{ic} + h(r_{ic}) + \phi_{cq^*} + \nu_{ic} \tag{4}$$

$$Y_{ic} = \gamma_2 C_{ic} + g(r_{ic}) + \eta_{cq^*} + \varepsilon_{ic} \tag{5}$$

where C is an indicator for enrollment at any exam school in the year following application

from the sample of students used to compute estimated effects on PSAT math scores in Table 5 below.

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.

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.

Importantly, there must be no manipulation of the forcing variable, in this case SHSAT score, around the cutoff. 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 interval 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. Additionally, I explore heterogeneity by sex in Section 5.2 and find no evidence that exam school effects for male and female students are statistically different.

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 effects using Equation 1. For each outcome, the first row corresponds to the "Any Offer" regression discontinuity

estimate with robust standard errors in parenthesis below, and the third and fourth rows report counterfactual means and sample size, respectively.[28] Test score results are shown in Columns (1)-(4). With respect to PSAT math scores, there is a jump at the cutoff of approximately 0.16σ. Turning to SAT math scores, the jump at the cutoff is a marginally

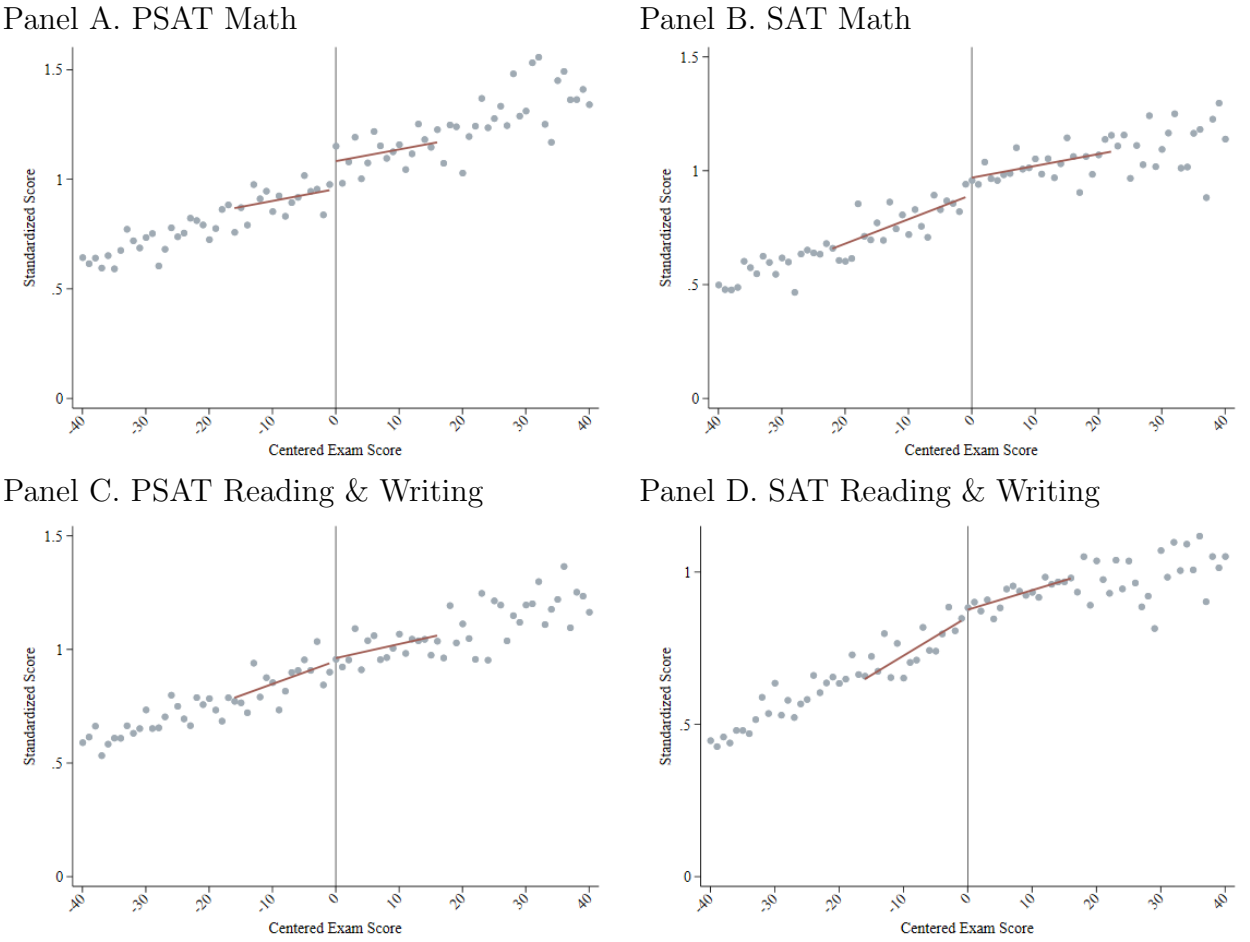


Figure 4: Relationship Between Centered Exam Scores and Standardized Test Scores

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.

statistically significant 0.07σ. 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

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

and SAT-MCAS) by 0.16σ and 0.07σ, respectively.[29] As shown in Figure 4, estimates for 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.

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. 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). As shown in the left panel of Figure 5, students experience a

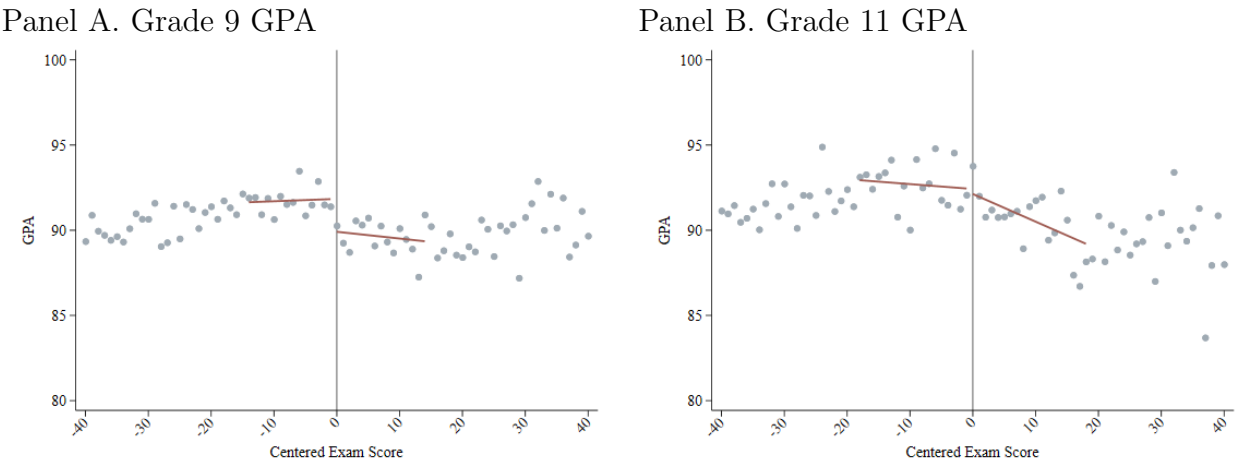


Figure 5: Relationship Between Centered Exam Scores and High School GPA

Notes: This figure illustrates the effect of being eligible for any Discovery Program on GPA in grades 9 and 11. 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.

negative impact of Discovery invites on ninth grade GPA. 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),

[29]The Massachusetts Comprehensive Assessment System (MCAS) is the state's mandatory high school graduation exam for the sample period used by Ellison and Pathak (2025).

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 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.

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 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. 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.

[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."

[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.

Table 2: Discovery Program RD Estimates

	PSAT		SAT		GPA		AP Exams	
	Math (1)	Reading (2)	Math (3)	Reading (4)	Grade 9 (5)	Grade 11 (6)	All Exams (7)	Popular Exams (8)
Panel A: Reduced Form (ITT)								
Any Offer	0.156***	0.025	0.071*	0.021	-1.885***	-0.240	-1.707	-0.872
	(0.044)	(0.044)	(0.041)	(0.043)	(0.629)	(0.799)	(1.176)	(0.911)
Counterfactual Mean	0.90	0.86	0.76	0.75	91.7	92.7	14.3	11.4
N	3,401	3,401	3,562	2,661	3,146	3,075	1,450	1,337
Panel B: 2SLS (LATE)								
Any Offer	0.277***	0.044	0.128*	0.040	-3.664***	-0.467	-4.550	-2.378
	(0.077)	(0.078)	(0.073)	(0.083)	(1.207)	(1.542)	(3.160)	(2.491)
First Stage F	508.8	481.4	503.3	353.1	426.6	387.3	110.89	103.6
N	3,401	3,401	3,562	2,661	3,146	3,075	1,450	1,337

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 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 5, 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 0.28σ 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 for estimates, I find no effect on eleventh grade GPA or AP exam scores.

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

5.2 Heterogeneity

In this section, I explore whether exam schools have heterogeneous impacts on male and female students. I begin by looking at estimates of exam school effects that vary with whether an applicant is female. Panel A of Table 3 reports reduced form estimates using a specification that includes an interaction term between the any-offer indicator and an indicator for whether an applicant is female. Across the board, I find no statistically significant differences of exam school effects between male and female students.

Table 3: Reduced Form Heterogeneity by Sex

	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: Interaction								
Any Offer	0.126**	0.049	0.086*	0.021	-1.944***	-0.072	-2.388*	-1.261
	(0.051)	(0.051)	(0.046)	(0.051)	(0.733)	(0.949)	(1.387)	(1.053)
Any Offer × Female	0.036	-0.035	-0.043	0.002	0.526	-0.046	1.423	0.887
	(0.047)	(0.046)	(0.043)	(0.044)	(0.630)	(0.804)	(1.234)	(0.951)
N	3,401	3,401	3,562	2,661	3,146	3,075	1,450	1,337
Panel B: Female								
Any Offer	0.199***	0.023	0.106*	0.069	-1.342	0.120	-0.683	0.130
	(0.061)	(0.060)	(0.061)	(0.049)	(0.824)	(1.040)	(1.624)	(1.222)
N	1,531	1,451	1,535	1,620	1,363	1,361	676	714
Panel C: Male								
Any Offer	0.109*	0.030	0.033	-0.012	-1.938**	-0.223	-2.333	-1.253
	(0.061)	(0.060)	(0.061)	(0.069)	(0.829)	(1.369)	(1.590)	(1.190)
N	1,752	1,752	1,646	1,266	2,101	1,317	925	860

Notes: This table presents reduced form (ITT) estimates exploring heterogeneity by applicant sex. Panel A reports estimates of the any offer indicator and its interaction with a dummy variable indicating that is equal to one if a student is identified as female and zero if male. The bandwidth selection and analysis sample correspond to that of the main estimates presented in Table 2. Panel B reports estimates of Equation 1 on a sample restricted to female applicants and Panel C reports estimates on a sample restricted to male applicants. For estimates reported in Panels B and C, 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%.

Next, I split the sample and estimate reduced form effects for male and female students separately. Motivated by the main findings on standardized test outcomes in math, Figure 6 depicts exam school effects on PSAT and SAT math scores for male and female students separately. The panels in the left column (Panels A and C) show RD estimates for male students and those in the right column (Panels B and D) for female students. In the sample of female students, there is a large jump in PSAT math scores at the qualifying cutoff. The

formal estimates reported in Table 3 suggest that female students who clear their qualifying cutoff experience a 0.2σ increase in PSAT math scores. For male students, this effect is a smaller but meaningful 0.11σ (statistically significant at the 10 percent level).

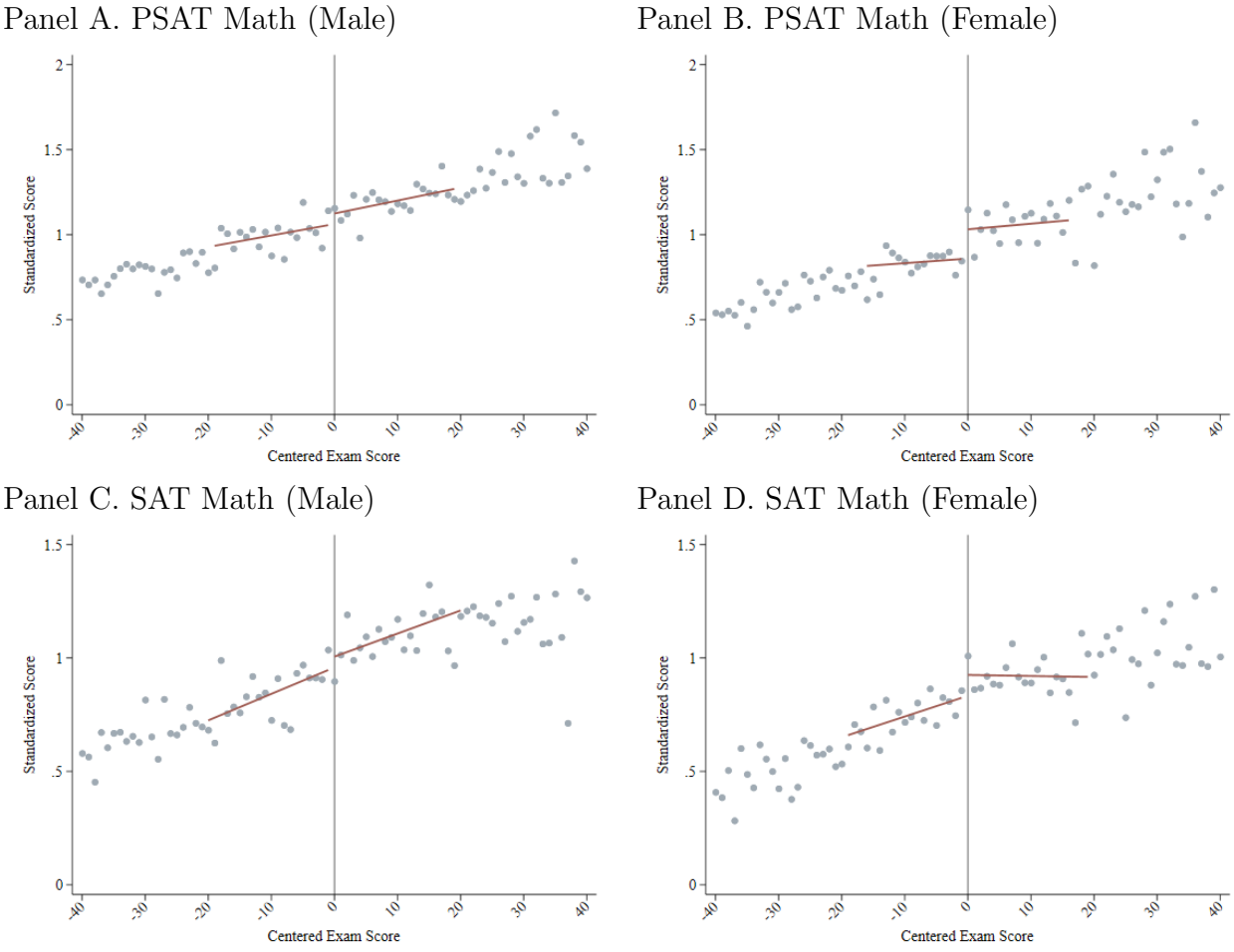


Figure 6: Math Score Heterogeneity by Sex

Notes: This figure illustrates the effect of being eligible for any Discovery Program on PSAT and SAT scores in math. Panels A and C on the left show the effect on math scores for male students and Panels B and D on the right show the effect for female students. The top two panels report PSAT math results and the bottom panels report SAT math 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.

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 estimate for male students, 0.03σ, is small and not distinguishable from zero. I find no effect of reserve seat eligibility on PSAT or SAT reading scores for male or female

students.

Lastly, I break down exam school effects on GPA. Figure 7 illustrates the effect of Discovery Program eligibility on GPA in grade 9 and grade 11 for male and female students. Panel A shows a considerable drop in grade 9 GPA for male students. The estimate is 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.

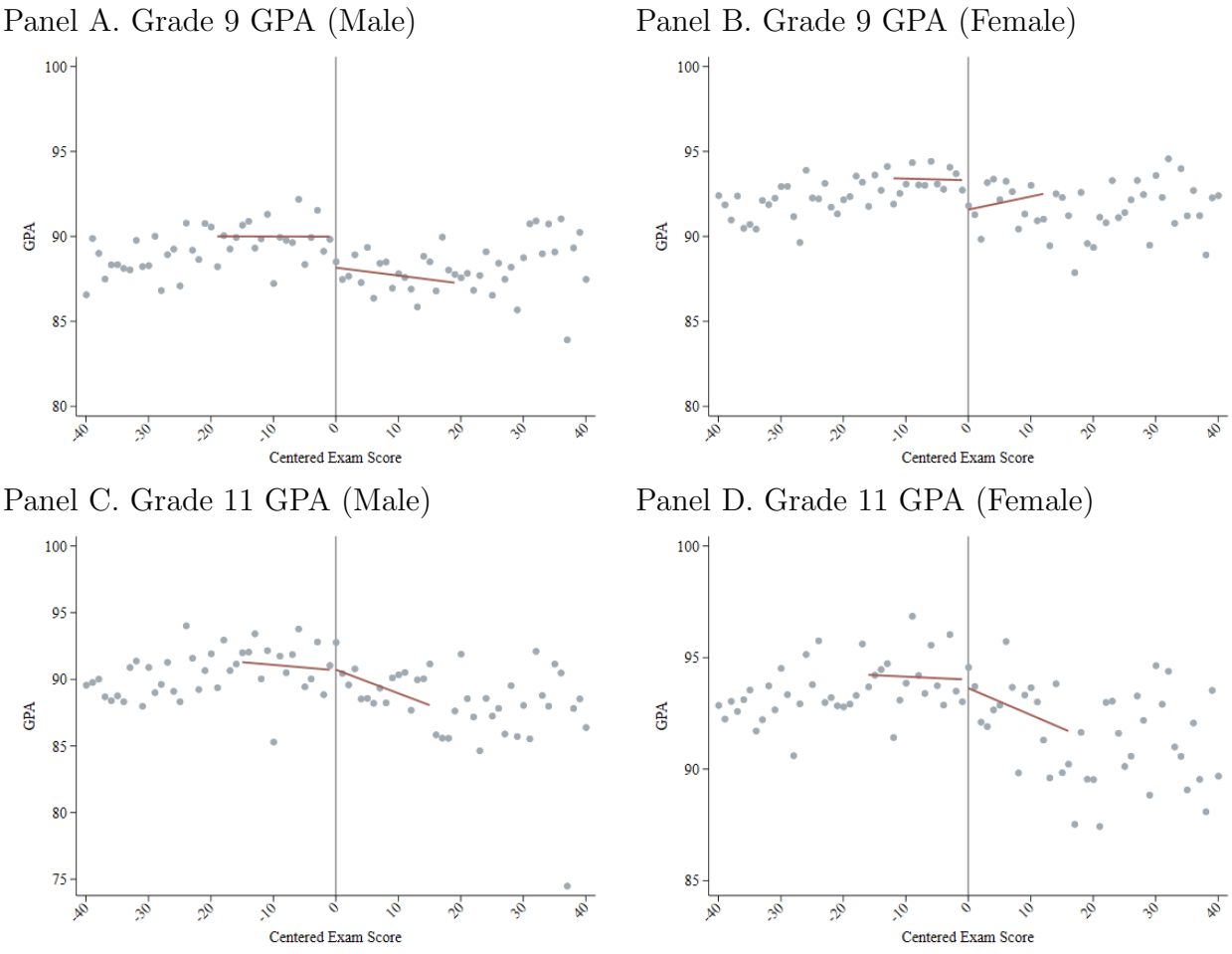


Figure 7: GPA Heterogeneity by Sex

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 male students and Panels B and D on the right show the effect for female 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.

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 A2 and A3 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.

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. Panel A reports the main estimates presented in Table 2, which use a local linear function of the running variable controls. Panel B 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. Adding these covariates does not add much precision to the test score estimates but does slightly attenuate them. The grade 9 GPA estimate remains unchanged and the AP exam estimates become more negative. However, the AP exam score samples are smaller and, as shown in Appendix Figure A3, the estimates may be sensitive to bandwidth selection. Panel C reports estimates using a quadratic relationship between the running variable and each outcome. Panel D reports estimates using the global quartic function specified in Equation 3. 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 0.16σ using the preferred maximum score to 0.9σ 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.

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

[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.

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.[34] I then increase the enrollment cap on immediate offers by the number of students in reserve seats and collapse the offer allocation process described above to the

[34] Appendix Figure A4 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.

first stage. Each applicant is assigned up to one offer under the counterfactual of no reserve 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.

Table 4 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 4: Pushed Out Enrollment Patterns

	Counterfactual Offer							
	Stuyvesant	Brooklyn Tech	Bronx Science	MSE City College	Lehman College	Queens Science	Staten Island Tech	Brooklyn Latin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Enrollment								
Stuyvesant	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.107
Brooklyn Tech	0.278	0.013	0.440	0.479	0.290	0.467	0.688	0.088
Bronx Science	0.356	0.004	0.000	0.049	0.000	0.000	0.000	0.044
MSE City College	0.043	0.000	0.069	0.000	0.000	0.000	0.021	0.009
Lehman College	0.007	0.000	0.116	0.080	0.000	0.022	0.000	0.004
Queens Science	0.032	0.002	0.082	0.018	0.010	0.000	0.000	0.014
Staten Island Tech	0.127	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	0.845	0.237	0.711	0.644	0.366	0.498	0.708	0.281
N	536	2,323	698	163	210	229	336	1,352

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 4 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. This can be seen in the first row of Figure 8, 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

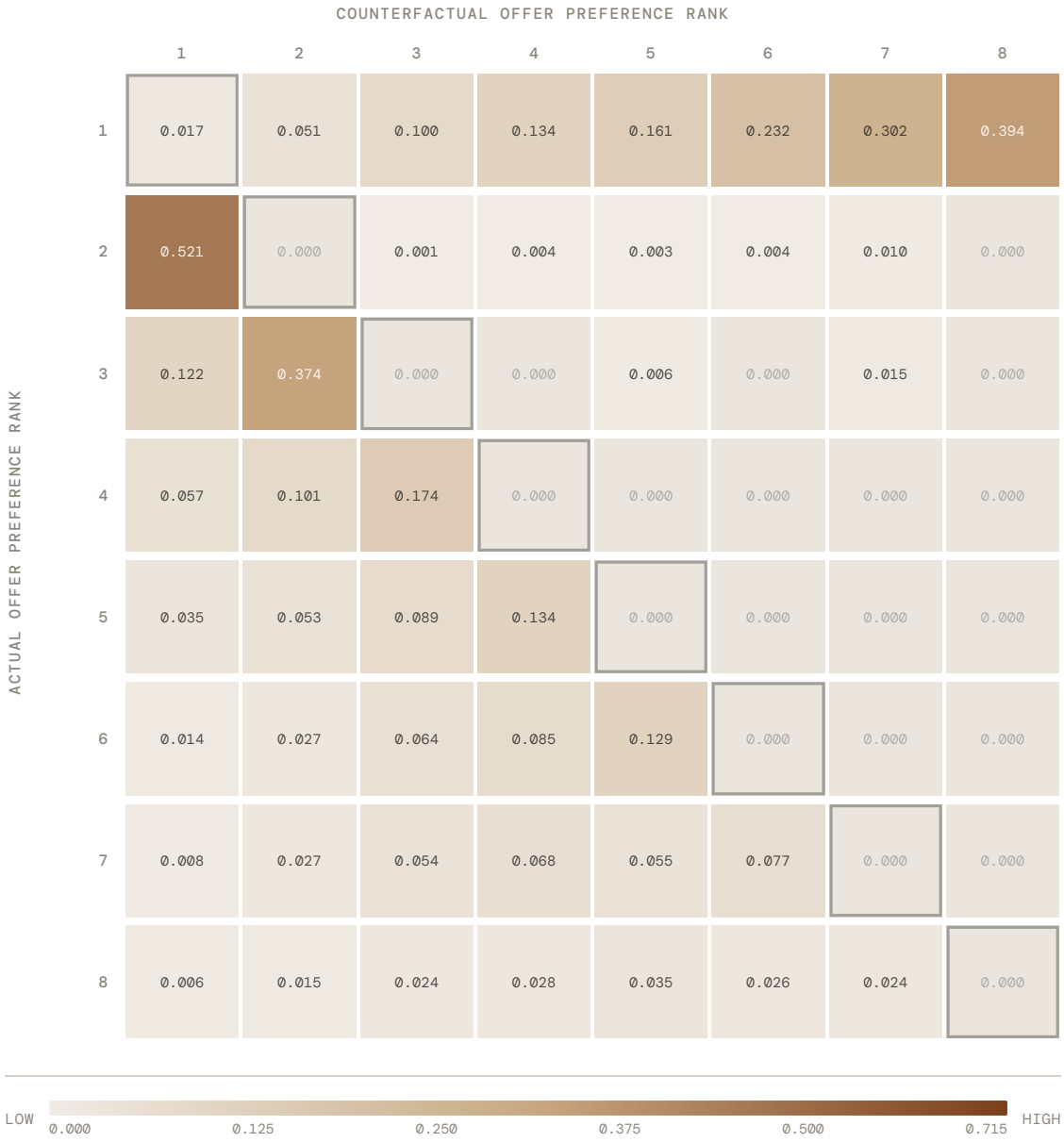


Figure 8: Enrollment Rank Distribution by Counterfactual Offer Preferences

Notes: This figure presents a matrix of Specialized High School enrollment patterns by 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. Rows represent the proportion of students in each column that enroll in the eight possible preference rankings.

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.

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. Figure 8 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 an eight choice. This pattern also reflects the fact that not all students rank all eight schools.

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 county, 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.

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.

References

Abdulkadiroğlu, A., Angrist, J., and Pathak, P. (2014). The elite illusion: Achievement effects at boston and new york exam schools. *Econometrica*, 82:137–196.

Abdulkadiroğlu, A., Angrist, J. D., Narita, Y., Pathak, P. A., and Zarate, R. A. (2017). Regression discontinuity in serial dictatorship: Achievement effects at chicago's exam schools. *American Economic Review: Papers & Proceedings*, 107:240–245.

Abdulkadiroğlu, A., Pathak, P. A., and Roth, A. E. (2005). The new york city high school match. *American Economic Review: Papers & Proceedings*, 95:364–367.

Ajayi, K. F. (2014). Does school quality improve student performance? new evidence from ghana.

Allensworth, E. M., Moore, P. T., and de la Torre, M. (2017). The educational benefits of attending higher performing schools: Evidence from chicago high schools. *Educational Evaluation and Policy Analysis*, 39:175–197.

Angrist, J. D., Pathak, P. A., and Zarate, R. A. (2023). Choice and consequence: Assessing mismatch at chicago exam schools. *Journal of Public Economics*, 223:104892.

Angrist, J. D. and Rokkanen, M. (2015). Wanna get away? regression discontinuity estimation of exam school effects away from the cutoff. *Journal of the American Statistical Association*, 110(512):1331–1344.

Arcidiacono, P., Aucejo, E. M., Fang, H., and Spenner, K. I. (2011). Does affirmative action lead to mismatch? a new test and evidence. *Quantitative Economics*, 2(3):303–333.

Arcidiacono, P. and Lovenheim, M. (2016). Affirmative action and the quality-fit trade-off. *Journal of Economic Literature*, 54:3–51.

Arcidiacono, P., Lovenheim, M., and Zhu, M. (2015). Affirmative action in undergraduate education. *Annual Review of Economics*, 7(Volume 7, 2015):487–518.

Barrow, L., Sartain, L., and de la Torre, M. (2020). Increasing access to selective high schools through place-based affirmative action: Unintended consequences. *American Economic Journal: Applied Economics*, 12:135–163.

Barrow, L. and Schanzenbach, D. W. (2012). Education and the poor. In *The Oxford Handbook of the Economics of Poverty*. Oxford University Press.

Belasco, A. S., Rosinger, K. O., and Hearn, J. C. (2015). The test-optional movement at america's selective liberal arts colleges: A boon for equity or something else? *Educational Evaluation and Policy Analysis*, 37(2):206–223.

Bennett, C. T. (2022). Untested admissions: Examining changes in application behaviors and student demographics under test-optional policies. *American Educational Research Journal*, 59(1):180–216.

Beuermann, D. W. and Jackson, C. K. (2022). The short- and long-run effects of attending the schools that parents prefer. *Journal of Human Resources*, 57(3):725–746.

Beuermann, D. W., Jackson, C. K., Navarro-Sola, L., and Pardo, F. (2022). What is a good school, and can parents tell? evidence on the multidimensionality of school output. *The Review of Economic Studies*, 90(1):65–101.

Black, S. E., Denning, J. T., and Rothstein, J. (2023). Winners and losers? the effect of gaining and losing access to selective colleges on education and labor market outcomes. *American Economic Journal: Applied Economics*, 15(1):26–67.

Bleemer, Z. (2022). Affirmative action, mismatch, and economic mobility after california's proposition 209*. *The Quarterly Journal of Economics*, 137(1):115–160.

Bleemer, Z. (2023). Affirmative action and its race-neutral alternatives. *Journal of Public Economics*, 220:104839.

Borghesan, E. (2022). The heterogeneous effects of changing sat requirements in admissions: An equilibrium evaluation.

Cabrera-Hernández, F. J., Dustan, A., Osuna Gomez, D., and Padilla-Romo, M. (2026). Marginal admission to elite high schools: Long-run effects on labor market outcomes. Working Paper 34706, National Bureau of Economic Research.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82:2295–2326.

Cattaneo, M. D., Jansson, M., and Ma, X. (2018). Manipulation testing based on density discontinuity. *The Stata Journal*, 18:234–261.

Cheng, S. and Weingarten, Z. (2025). Designing optimal school choice admissions policies: Insights from a lottery-based reform.

Clark, D. (2010). Selective schools and academic achievement. *The B.E. Journal of Economic Analysis & Policy*, 10.

Corcoran, S. P. and Baker-Smith, E. C. (2018). Pathways to an elite education: Application, admission, and matriculation to new york city's specialized high schools. *Education Finance and Policy*, 13:256–279.

Coull, S. (2019). My experience at stuy summer discovery. *The Stuyvesant Spectator*, 110.

Deming, D. J. (2022). Four facts about human capital. *Journal of Economic Perspectives*, 36(3):75–102.

Dobbie, W. and Fryer, R. G. (2014). The impact of attending a school with high-achieving peers: Evidence from the new york city exam schools. *American Economic Journal: Applied Economics*, 6:58–75.

Dur, U., Pathak, P. A., and Sönmez, T. (2020). Explicit vs. statistical targeting in affirmative action: Theory and evidence from chicago's exam schools. *Journal of Economic Theory*, 187:104996.

Dustan, A., de Janvry, A., and Sadoulet, E. (2017). Flourish or fail? the risky reward of elite high school admission in mexico city. *The Journal of Human Resources*, 52:756–799.

Ellison, G. and Pathak, P. A. (2021). The efficiency of race-neutral alternatives to race-based affirmative action: Evidence from chicago's exam schools. *American Economic Review*, 111:943–75.

Ellison, G. and Pathak, P. A. (2025). Optimal school system and curriculum design: Theory and evidence. *NBER Working Paper No. 34091*.

Epple, D., Romano, R., and Sieg, H. (2008). Diversity and affirmative action in higher education. *Journal of Public Economic Theory*, 10(4):475–501.

Faenza, Y., Gupta, S., and Zhang, X. (2023). Discovering opportunities in new york city's discovery program: Disadvantaged students in highly competitive markets.

Goodman, J., Gurantz, O., and Smith, J. (2020). Take two! sat retaking and college enrollment gaps. *American Economic Journal: Economic Policy*, 12:115–58.

Hu, W. (2018). Elite new york high schools to offer 1 in 5 slots to those below cutoff. *The New York Times*.

Jackson, C. K. (2010). Do students benefit from attending better schools? evidence from rule-based student assignments in trinidad and tobago. *The Economic Journal*, 120:1399–1429.

Jackson, C. K., Porter, S. C., Easton, J. Q., Blanchard, A., and Kiguel, S. (2020). School effects on socioemotional development, school-based arrests, and educational attainment. *American Economic Review: Insights*, 2(4):491–508.

Kapor, A. (2024). Transparency and percent plans. *NBER Working Paper No. 32372*.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48:281–355.

Lucas, A. M. and Mbiti, I. M. (2014). Effects of school quality on student achievement: Discontinuity evidence from kenya. *American Economic Journal: Applied Economics*, 6:234–263.

Luflade, M. and Zaiem, M. (2024). Do elite schools improve students performance? evidence from tunisia. *Economics of Education Review*, 100:102542.

Murphy, M. C. (1974). Academic implications of a high school entrance examination for economically disadvantaged and other students. *The Journal of Educational Research*, 67:303–306.

Pop-Eleches, C. and Urquiola, M. (2013). Going to a better school: Effects and behavioral responses. *American Economic Review*, 103:1289–1324.

Rokkanen, M. (2015). Exam schools, ability, and the effects of affirmative action: Latent factor extrapolation in the regression discontinuity design. *Columbia University*, Department

of Economics Discussion Paper 1415-03.

Rouse, C. E. and Barrow, L. (2006). U.s. elementary and secondary schools: Equalizing opportunity or replicating the status quo? *The Future of Children*, 16(2):99–123.

Rucinski, M. and Goodman, J. (2022). Racial diversity and measuring merit: Evidence from boston's exam school admissions. *Education Finance and Policy*, 17:408–431.

Sander, R. H. (2004). A systemic analysis of affirmative action in american law schools. *Stanford Law Review*, 57:367–483.

Schochet, P., Cook, T., Deke, J., Imbens, G., Lockwood, J. R., Porter, J., and Smith, J. (2010). Standards for regression discontinuity designs. page Retrieved from What Works Clearinghouse website: https://ies.ed.gov/ncee/wwc/Docs/ReferenceResources/wwc_rd.pdf.

Shapiro, E. (2019). A few more black students are offered spots at stuyvesant, fanning fresh uproar. *The New York Times*.

Shapiro, E. and Wang, V. (2019). Amid racial divisions, mayor's plan to scrap elite school exam fails. *The New York Times*.

Shi, Y. (2020). Who benefits from selective education? evidence from elite boarding school admissions. *Economics of Education Review*, 74:101907.

The Editorial Board (2024). Dissecting the discovery program. *The Stuyvesant Spectator*, 15.

Zimmer, A. (2023). Black and latino enrollment in nyc specialized high school integration program still lags. *Chalkbeat New York*.

Online Appendix to:

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

Michael Darisse

March 24, 2026

A Appendix Figures and Tables

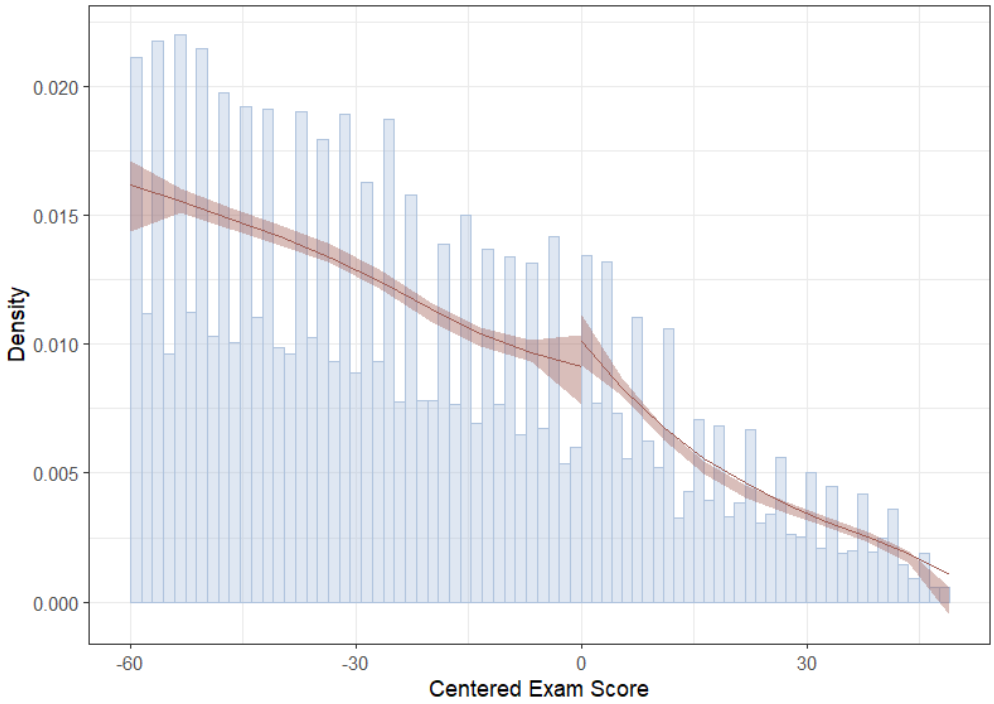
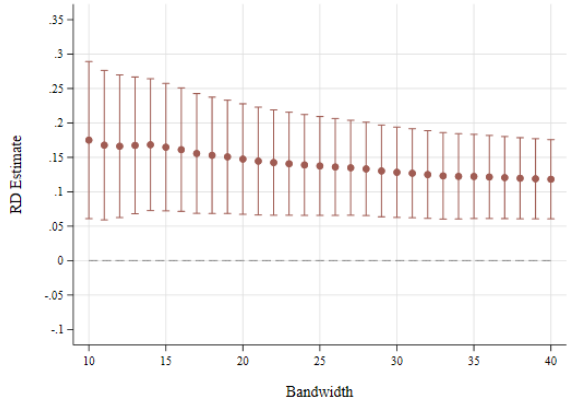


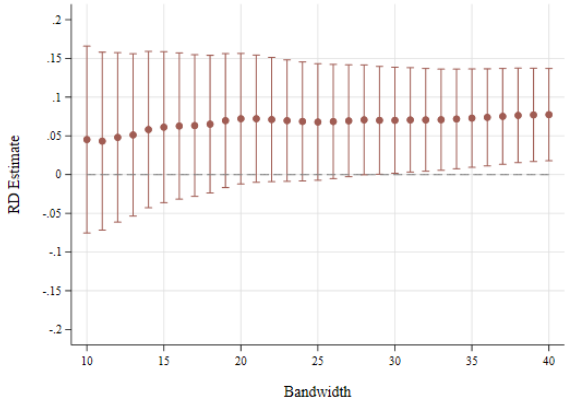
Figure A1: Running Variable Density Plot

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.

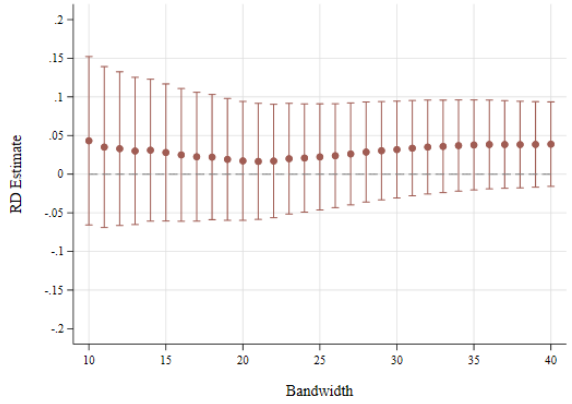
Panel A. PSAT Math



Panel B. SAT Math



Panel C. PSAT Reading & Writing



Panel D. SAT Reading & Writing

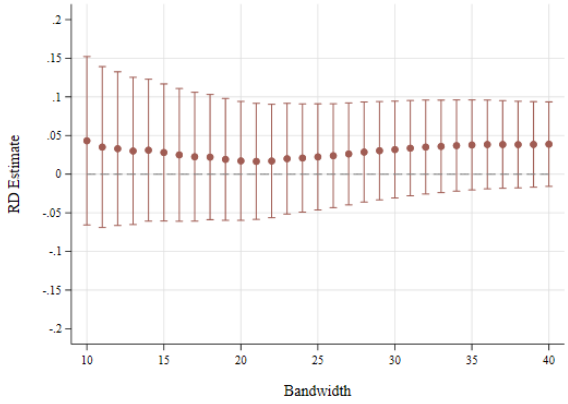
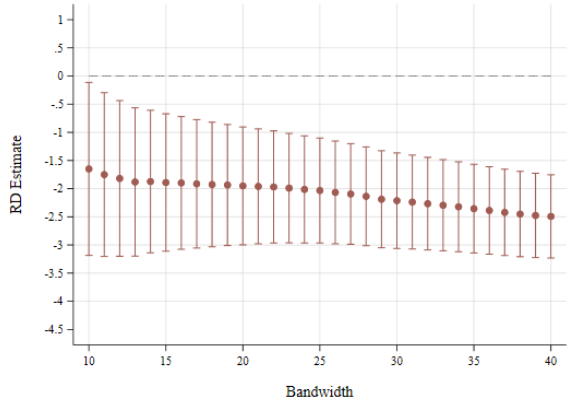


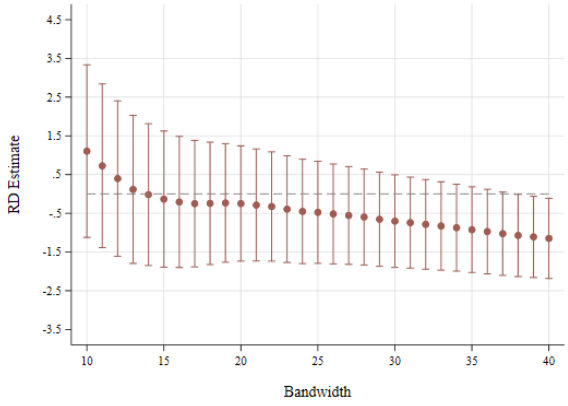
Figure A2: Bandwidth Sensitivity I

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).

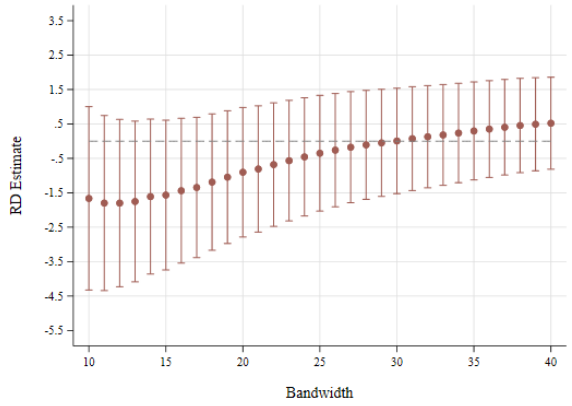
Panel A. Grade 9 GPA



Panel B. Grade 11 GPA



Panel C. All AP Exams



Panel D. Popular AP Exams

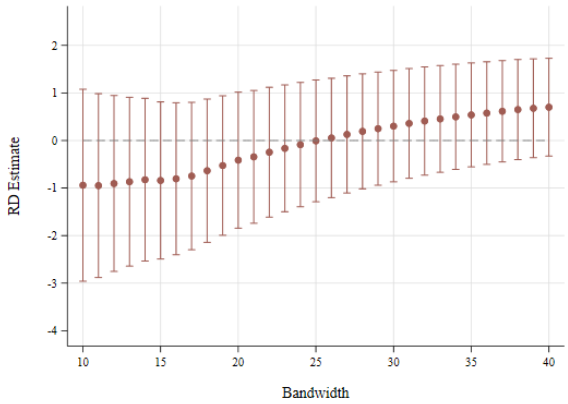


Figure A3: Bandwidth Sensitivity II

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).

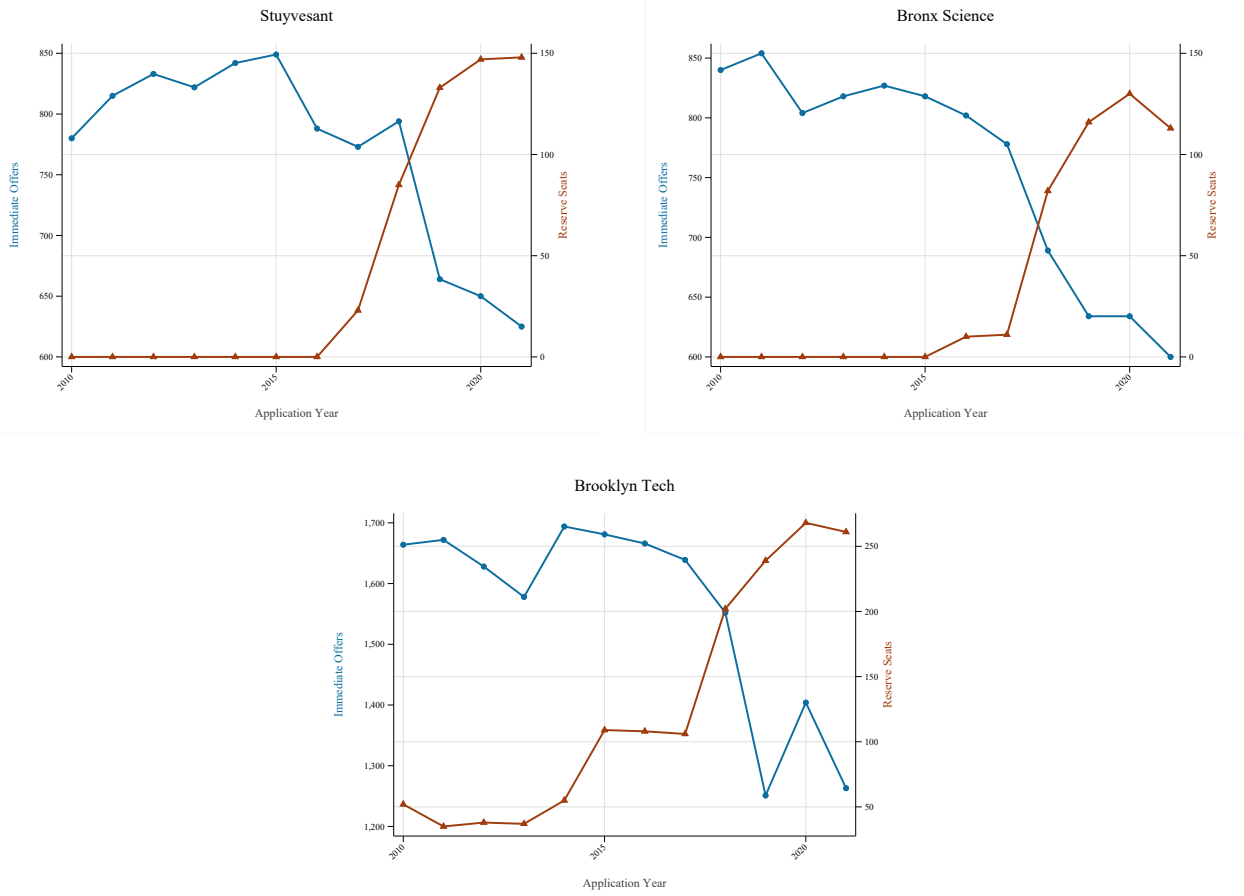


Figure A4: "Big 3" Enrollment Trends by Seat Type

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.

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	
	Math	Reading	Math	Reading	Grade 9	Grade 11	All Exams	Popular Exams
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: First Stage								
Enrollment	0.540***	0.540***	0.577***	0.529***	0.537***	0.550***	0.520***	0.507***
	(0.021)	(0.021)	(0.021)	(0.024)	(0.023)	(0.023)	(0.030)	(0.031)
N	3,786	3,786	4,048	3,022	3,350	3,359	1,867	1,740
Panel B: Reduced Form (ITT)								
Any Offer	0.129***	0.012	0.060	0.028	-1.950***	-0.151	-1.030	-0.682
	(0.041)	(0.039)	(0.037)	(0.039)	(0.575)	(0.710)	(1.101)	(0.865)
N	3,041	3,041	3,562	2,661	3,146	3,075	1,450	1,337
Panel C: 2SLS (LATE)								
Any Offer	0.218***	0.021	0.101	0.051	-3.509***	-0.266	-2.218	-1.502
	(0.069)	(0.066)	(0.061)	(0.070)	(1.023)	(1.242)	(2.365)	(1.904)
N	3,041	3,041	3,562	2,661	3,146	3,075	1,450	1,337

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

	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: Primary Estimates								
Any Offer	0.156***	0.025	0.071*	0.021	-1.885***	-0.240	-1.707	-0.872
	(0.044)	(0.044)	(0.041)	(0.043)	(0.629)	(0.799)	(1.176)	(0.911)
Panel B: Additional Covariates								
Any Offer	0.135***	0.030	0.041	0.021	-1.889***	-0.356	-2.228**	-1.246
	(0.043)	(0.044)	(0.039)	(0.043)	(0.605)	(0.790)	(1.135)	(0.879)
Panel C: Quadratic								
Any Offer	0.189***	0.057	0.058	-0.005	-1.597*	0.733	-0.999	-0.370
	(0.065)	(0.063)	(0.060)	(0.065)	(0.966)	(1.229)	(1.724)	(1.309)
Panel D: Global Quartic								
Any Offer	0.180***	0.039	0.067	0.009	-1.861**	0.349	-1.880	-1.094
	(0.057)	(0.056)	(0.052)	(0.055)	(0.821)	(1.038)	(1.486)	(1.148)
Counterfactual Mean	0.90	0.86	0.76	0.75	91.7	92.7	14.3	11.4
N	3,401	3,401	3,562	2,661	3,146	3,075	1,450	1,337

Notes: This table reports reduced form (ITT) estimates using alternative specifications. Panel A reports the main estimates presented in Table 2, which use a local linear function of the running variable controls. Panel B 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. Panel C reports estimates using a quadratic relationship between the running variable and each outcome. Panel D reports estimates using the global quartic function specified in Equation 3. 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 Max. Total				
Any Offer	0.156***	0.025	0.071*	0.021
	(0.044)	(0.044)	(0.041)	(0.043)
N	3,401	3,401	3,562	2,661
Panel B: Superscore				
Any Offer	0.159***	0.028	0.076*	0.030
	(0.044)	(0.043)	(0.041)	(0.042)
N	3,394	2,872	3,562	3,097
Panel C: First Attempt				
Any Offer	0.094**	-0.029	0.057	0.021
	(0.041)	(0.044)	(0.038)	(0.038)
N	3,041	3,041	3,562	2,813

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%.

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.[35] 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

[35] 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.[36]

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.[37]

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

[36] College Board Concordance Tables for SAT scores.
[37] 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.

Graduation Data

In order to graduate, students in NY State must earn a certain number of credits in specified subject areas and receive a score of 65 or higher on their Regents examinations. There are three types of diplomas in NY State: A Regents diploma, advanced Regents diploma, and a local diploma. To receive a Regents diploma a student must receive the required score on the following five exams: ELA, any math exam (Algebra I, Geometry, or Algebra II/Trigonometry), any social studies exam (Global History and Geography or U.S. History and Government), any science exam (Living Environment, Chemistry, Earth Science, or Physics), and any additional Regents exam. To earn an advanced Regents diploma, students must score a 65 or higher on nine exams: ELA, three math exams, one social studies exam, two science exams (Living Environment and one of: Chemistry, Earth Science, or Physics), any NYC World Languages exam (also known as Languages Other Than English (LOTE) exam), and any additional Regents exam. The NYS graduation file contains information on each student's final graduation outcome and diploma type for those who earned one. The graduation files contain two entries for each student, one for outcomes recorded at the end of the academic year and another recorded in August. I use outcomes recorded in August to account for any changes in graduation status over the summer.

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.