Student Preferences and Horizontal Differentiation in Urban School Choice Markets

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Abstract: Many urban public school systems in the United States allow families to pick among schools with different academic themes. For example, New York City students can choose to attend high schools focused on topics as varied as health sciences, journalism, and performing arts. In this paper, I investigate the impact of curricular themes on segregation and student outcomes in New York City high schools. I estimate a structural model using data on student applications to determine how families trade off curricular themes and other school characteristics in the application process. I find that all demographic groups, but particularly white and Asian applicants, tend to prefer Humanities and Interdisciplinary programs, the most general curricular theme, to more specialized themes. Using the model to compare the baseline assignment to a simulated counterfactual assignment in which all programs are Humanities and Interdisciplinary, I find that curricular differentiation slightly increases racial segregation across programs. On average, students prefer their counterfactual assignment, but a substantial minority of applicants, including about half of all Black applicants, would be worse off without curricular differentiation. Finally, to provide a more complete picture of the trade-offs involved in offering curricular differentiation, I use quasi-experimental variation generated by the assignment mechanism to estimate theme enrollment effects. I find that theme matters for high school outcomes and postsecondary choice, but effects do not vary by theme preference, suggesting limited scope for themes to improve student-school match quality. [1]

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1 Introduction

In recent decades, urban school systems in the United States have expanded school choice and centralized assignment. Rather than defaulting to a neighborhood school, families are increasingly encouraged to actively choose among a broad set of schools with different attributes, express their preferences through an application process, and receive a school assignment from a coordinated mechanism. Proponents of school choice have highlighted its potential to increase access to high-quality schools across income and racial gaps[2].

While schools differ on measures like test scores, graduation rates, and other "vertical" indicators of quality, they are also horizontally differentiated. Families can choose schools in different locations, with different teaching philosophies, and with different curricula, dimensions along which preferences are likely to vary.

Urban school systems in the United States often feature a wide degree of curricular heterogeneity. Students can choose high schools focused on themes as diverse as performing arts, environmental science, and teaching. But while a vast literature has examined the implications of school choice for student sorting along demographic lines into higher or lower-quality schools, little is known about student preferences with respect to curricular themes.

This paper measures preferences for themed curricula and explores the implications of curricular differentiation for segregation and student outcomes in New York City high schools. First, I provide descriptive evidence on how school application and enrollment behavior with respect to curricular theme varies by race, income, and achievement. I then estimate a structural model of school program choice in which curricular theme enters applicant program utility, enabling me to quantify the extent to which applicants care about theme relative to other school characteristics. I use this model to measure the extent to which theme preferences contribute to cross-school segregation. Finally, I use exogenous variation generated by the school assignment mechanism to identify whether assignment to an applicant's preferred theme affects their high school outcomes.

School choice and differentiation enable the sorting of students into different types of schools. The history of unequal and racially segregated education in the United States motivates the question of whether choice and differentiation contribute to differential sorting across schools by income and race. Theme is one of many dimensions along which this differential sorting may occur, and the implications for segregation are ambiguous. Whether theme preferences contribute to segregation across demographic lines depends on the distribution of preferences for theme across and within demographic groups. If theme preferences differ drastically across demographic groups, relative to their variation within-group, it is possible that curricular differentiation increases segregation by encouraging students to sort into different schools along demographic lines. However, if families care about themes, and preferences over themes are distributed more similarly across demographic groups than preferences over other characteristics, themed schools could, on net, lead families from different backgrounds to choose more similar schools than they would otherwise. The latter idea

[2] A large literature has evaluated whether school choice lives up to this potential (see section 1.1).

has led to the use of curricular differentiation in conjunction with other policies to desegregate schools, both in post-*Board v. Brown* desegregation efforts in the 1970s as well as more recently (Bifulco, Cobb, and Bell 2009; Office of Elementary and Secondary Education 2024; Buder 1975).

We also do not know the implications of curricular differentiation for student outcomes. The first question of interest is whether different themes have different impacts on student test scores, graduation, or postsecondary enrollment. If this is the case, differential sorting into themed programs along demographic lines may have important implications for achievement gaps by income and race. The second question of interest is whether students experience theme match effects. It is possible that students learn better when they enroll at programs that align with their interests instead of programs that do not. If this is the case, we may observe that students with stronger preferences for a particular theme, relative to the other theme options, experience more positive impacts on achievement in that theme than students with weaker preferences for that theme. If students sort into themes based on expected achievement gains, curricular differentiation can even improve the efficiency of education production by increasing match quality.

The first step to answering these questions about the impacts of curricular differentiation is to better understand student preferences for themes. This paper uses administrative data from the New York City high school application match to measure theme preferences by race, income, and achievement. Prospective New York City high school students must apply via a centralized application system, submitting up to 12 schools ranked in order of preference, and receiving a single assignment from a Deferred Acceptance mechanism. In this setting, all schools are themed, though the largest theme category is a general, "Humanities and Interdisciplinary" theme in contrast with the more specialized themes. For each eighth grade applicant to high school, I observe demographic characteristics, rank-ordered list, high school assignment, high school enrollment, and high school outcomes.

I begin by presenting novel descriptive evidence on application and enrollment behavior with respect to theme by race, income and achievement. I find that white and Asian students, non-low-income students, and high baseline achievement students are more likely to enroll at Humanities and Interdisciplinary programs than others.

I then estimate a structural model of strategic application choice, allowing for rich heterogeneity by observable and unobservable applicant characteristics. I decompose program preferences to isolate the theme component, allowing me to measure how much applicants care about theme relative to other school characteristics. My model estimates are consistent with my descriptive evidence: while all applicants prefer Humanities and Interdisciplinary programs, relative to more specialized themes, white and Asian applicants have the strongest relative preference for Humanities and Interdisciplinary programs.

I simulate a counterfactual assignment without curricular differentiation, and explore who is worse or better off by comparing their program assignments. I find that while applicants on average are better off in the counterfactual where all programs are Humanities and Interdisciplinary programs, a substantial minority of applicants are worse off, including half of all Black applicants.

I also measure segregation in the counterfactual relative to the baseline. I find that removing curricular differentiation by making all programs Humanities and Interdisciplinary slightly reduces segregation along all dimensions. These results suggest that offering specialized theme programs encourages segregation, though the magnitudes of the effects are small.

Finally, I use quasi-random variation in theme assignment generated by the centralized assignment mechanism in order to identify the effect of enrolling at each theme on attendance, SAT taking, graduation in 4 years, and postsecondary enrollment. I then estimate these effects separately by relative theme preference (estimated by my model), in order to determine whether students sort on expected gains into specialized theme programs. While theme matters for high school outcomes, I do not find any evidence that theme effects vary by preference and facilitate better match quality.

1.1 Related Literature

1.1.1 Family preferences for schools

My paper contributes to a vast literature that examines what families care about when choosing schools and how families make these decisions. Abdulkadiroglu, Pathak, Schellenberg, and Walters (2020) find that parents care about proximity and baseline peer achievement, rather than school effectiveness. Using house prices, Black (1999) measures parents' willingness to pay for schools with higher test scores. Even in settings where all parents prefer high-performing schools, differences in distance to these schools or peer preferences may result in differences in how school performance must be traded off against these other characteristics, by income and race (Hastings, Kane, and Staiger 2008; Burgess, Greaves, Vignoles, and Wilson 2014). Families choosing high schools in New York City prefer schools where students are predominantly of the same race as them, independent of characteristics potentially correlated with race (Hailey 2022). Crespin (2023) finds that families are willing to trade off worse school-level test scores for a better school climate.

Other features of applicants' choice environment can influence their application and enrollment decisions. Corcoran, Jennings, Cohodes, and Sattin-Bajaj (2018) suggests information may be a barrier in the choice of high-performing schools, as low-income New York City middle school students responded in application and enrollment decisions to an information intervention in which they received a list of nearby, high-performing schools. In New York City, Hahm and Park (2022) finds that middle school assignment can affect students' high school enrollment, through its effect on high school application choices.

1.1.2 Horizontal school differentiation and student outcomes

My paper also contributes to a literature on horizontal differentiation and student outcomes. Career and Technical Education (CTE) is one form of curricular differentiation in schools. Previous work has documented heterogeneity in selection into CTE, as well as heterogeneity in its effect on high school and postsecondary outcomes (Brunner, Dougherty, and Ross 2021; Dougherty 2018; Jacob and Ricks 2023). In my setting, I consider CTE offerings to be part of the curricular differentiation captured by theme categorization.

Other papers have shed light on which school characteristics are correlated with effectiveness. Dobbie and Fryer (2013) find that frequent teacher feedback, the use of data to guide instruction, high-dosage tutoring, increased instructional time, and high expectations are correlated with charter school effectiveness. Bloom and Unterman (2014) find that enrollment at one of New York City's "small high schools of choice" increases graduation rates by 9.5 percentage points. Using a value-added framework, Wiswall, Stiefel, Schwartz, and Boccardo (2014) finds some evidence of a positive effect of enrollment in a STEM themed high school on STEM performance.

Student-school match quality can be seen as a form of horizontal differentiation, since it takes on different values for different students. In some contexts, students do sort on gains; Norwegian college applicants sort into postsecondary fields in which they have a comparative advantage (Kirkeboen, Leuven, and Mogstad 2016). On the other hand, Walters (2018) finds negative selection on gains into the charter middle school sector in Boston.

1.1.3 Magnet schools and desegregation

Previous work has examined whether themed magnet schools have worked to reduce segregation. Based on a descriptive analysis comparing districts from 1968 to 1991 that adopted desegregation plans with magnet schools versus without, Rossell (2003) concludes that magnet schools do not produce more interracial exposure. Bifulco et al. (2009) found that themed, inter-district magnet schools in an inner-ring suburb of Hartford, Connecticut reduced the racial and economic isolation for city students who enrolled there.

While some of the themed school in my setting, New York City, started out as magnet schools, they are now part of the same public high school centralized application and enrollment process as all other high schools. Students do not need to specially opt into specialized themed schools in my setting, as all schools are part of the same application process. Unlike the studies of magnet schools, my setting in which all schools are themed enables me to focus specifically on theme preferences, and the contribution of these preferences to segregation.

1.1.4 Structural determinants of school segregation

My paper also contributes to a literature on contributors to present-day school segregation. Monarrez (2023) finds that residential segregation explains more than 100 percent of school segregation, with local government policy promoting integration having relatively little effect. Even in school choice contexts meant to equalize access, selective admissions and differential distance to high-quality schools contribute to segregation (Idoux 2021; Laverde 2022). Monarrez, Kisada, and Chingos (2022) find that the proliferation of charter schools may have increased cross-school segregation, it may have also decreased cross-district segregation in the largest metropolitan areas. Caetano and Macartney (2021) finds that much of school segregation is driven by neighborhood factors in residential choice, rather than school choice itself. Oosterbeek, Sovago, and Klaauw (2021) find that in Amsterdam, 40% of school segregation by ethnicity and 25% of school segregation by household income can be attributed to preference heterogeneity.

2 Setting: New York City Public Schools

The setting of my study is the New York City high school application and assignment system. In this section, I provide some historical and present-day context about the New York City public school system, list the themes available to high schoolers, and describe the application and assignment process for high school.

2.1 Historical and Institutional Context

The New York City public school system is the largest school system in the United States, serving over 1 million students in over 1800 schools in 2022-23 (NYC Department of Education 2024a). 73 percent of these students are economically disadvantaged, and 85 percent are nonwhite (in comparison, public school students in New York State are 58 percent economically disadvantaged are 60 percent nonwhite) (NYC Department of Education 2024a; New York State Education Department 2024). While New York City 8th graders score below average in reading and math compared to other districts in the nation, they perform better than average among large city districts (NYC Department of Education 2024b).

The current landscape of choice in New York City public high schools owes much of its shape to 2000s era reforms, taking place under the leadership of the mayor, Michael Bloomberg and the Department of Education Chancellor, Joel Klein. While a large degree of choice existed before 2003, choice was largely limited to students who opted in; students unaware of or disinterested in choosing an alternative option could simply enroll at their default, zoned school. Starting in 2003-2004, all students were required to participate in the centralized assignment system and fill out a rank-ordered application list. The assignment mechanism changed from being uncoordinated to coordinated, with students receiving a single offer. Zoned schools eventually were phased out, and applicants were largely eligible to enroll at any school in the city. From this time onwards, all high school programs were assigned a theme category.

The non-general curriculum, specialized theme high schools in our sample were established both before and around the time of this change. Some social justice oriented high schools were founded in the 1960s and 1970s by progressive teachers who were influenced by the Civil Rights movement (Hemphill and Nauer 2009). Around the same time, in response to concerns about the exodus of white families from city public schools, school officials introduced themed schools in an attempt to create programs that would appeal to student interests and attract white families to majority black schools (Buder 1975). A second wave of themed programs were established in the mid-2000s, when Bloomberg and Klein partnered with the Gates Foundation to address the issue of large, underperforming high schools, closing several of these schools with graduation rates below 45 percent. In their stead, they established several new small high schools with themed course offerings, oriented around areas such as technology, the arts, business, law, or hospitality. The themed offerings were designed to empower students to choose an educational program in alignment with their interests and career aspirations. They were also designed to take advantage of the expertise and resources of teachers potentially attracted by the theme, and partner organizations (e.g., a law firm associated with a law-and-justice themed school) (Quint, Smith, Unterman, and Moedano 2010).

2.2 Theme Categorization in this Study

Today, school program themes are self-reported to the Department of Education by schools, and there are no accountability measures or guidelines governing theme implementation. Regardless of how the themes are implemented, the theme labeling itself can have implications for the sorting of students. In the future, I intend to conduct descriptive analyses to shed light on how themed curricula differ in practice by looking at how the distribution of credits by subject area differs by theme.

I define nine academic themes for high school programs in New York City: Arts and Design; Business, Hospitality, and Services; Computing and Engineering; Humanities and Interdisciplinary; Media; Military and Law Enforcement; Multicultural; Public Service, Law, and Social Justice; and Science. Based on consultation with the New York City Department of Education, I defined the themes largely based on the academic interest areas listed in the high school directory, as well as the name of the program. I describe more about how I defined themes in Appendix A.

2.3 Application

I study themes in New York City high schools from 2011-2017. In New York City, since the 2003-2004 school year, every eighth grader applies to high school through a centralized and coordinated assignment mechanism. Rather than applying to schools, students apply to “programs” at schools, which are categorized by theme. About one in four schools have multiple programs, and of these, the median school has three programs. Students are given a printed with information on each program, organized by borough [3]. They must submit a rank-ordered application list of up to 12 programs, in order of preference [4]. The application may be submitted online, through the applicant’s middle school counselor, or through one of several Family Welcome Centers throughout the city.

Over the time period of my study, New York City students do not necessarily have a “zoned” neighborhood high school, so there is not necessarily a “default” option for students choosing high schools. Even students who do live in an area with a zoned high school need to apply to it through the same centralized application system. There are relatively few high school eligibility

[3] During my time period of study, this booklet was also available as a PDF online, in several languages. In the middle of my time period, an online search tool called MySchools was introduced that enables students to search for high school programs by characteristic of interest.

[4] On its website, the Department of Education instructs students, “it is very important to list your choices in your true order of preference — there is no better strategy” (NYC Department of Education 2023).

restrictions; while there exist a few single-sex or zoned programs, applicants are able to apply to the vast majority of high school programs.

There are a variety of admissions methods by which high schools determine who is assigned to their programs. Broadly, these methods either choose applicants via Lottery, or by ranked score based on various criteria (Score). These criteria can include middle school grades, attendance, and test scores, or additional application materials like an audition or essay. Lottery admission methods include Zoned, Unscreened, and Limited Unscreened. Score admission methods include Audition, Screened, and Screened for Language. The Education Option admissions method uses a combination of lottery and score ranks to admit students. Programs employing any of these methods group students by "priority" levels, applying the admit rule within priority group for students in descending levels of priority.

In short, the New York City high school application process involves applicants choosing and ranking programs, and programs ranking applicants. In the following subsection, I describe how these ranks are transformed into a single program assignment for each applicant.

2.3.1 Deferred Acceptance algorithm

The centralized assignment system is an implementation of the Deferred Acceptance algorithm. The main round of the assignment works as follows. Until every student is assigned, or has exhausted their ranked list, it repeats the following two steps:

1. Each student "proposes" to their best choice of the programs that have not yet rejected them. High school programs tentatively assign all of their seats in order of applicant priority. Ties within priority group are broken by lottery number or score rank. If more students propose than the program capacity, remaining proposals are rejected.

2. Students rejected in the current iteration propose to the next program on their list in the next iteration. Students tentatively assigned to a program seat propose to the same program in the next iteration.

After the algorithm terminates, some students may not have an assignment, if they were rejected from every program they listed. All students, including unassigned students, have the option of participating in a supplementary round, in which students rank programs with capacity still remaining, and are assigned according to the same algorithm. Students who are unassigned after the supplementary round are administratively placed into programs remaining capacity.

2.4 Assignment and Enrollment

Students receive a single assignment from the centralized assignment process. The New York City public school system also includes eight specialized exam schools, and one specialized audition school. I refer to these schools throughout as "Exam / Audition" schools[5]. Admission to these

[5] Exam / Audition includes the following schools: The Bronx High School of Science, The Brooklyn Latin School, Brooklyn Technical High School, Fiorello H. LaGuardia High School of Music & Art and Performing Arts, High

schools does not operate through the centralized assignment mechanism described above. Instead, students are invited to apply to the Exam / Audition schools in a parallel process. If they receive an offer from an Exam / Audition school, and the main high school assignment system, they can choose where they want to enroll. Alternatively, students can enroll at a New York City charter school, a private school, or a public school outside of New York City.

3 Data

I use administrative data from the New York City Department of Education. My population of interest is New York City 8th grade applicant cohorts from 2011-12 to 2017-18. I receive demographic information on these 8th grade students, including gender, race, eligibility for free or reduced price lunch, receipt of special education services, and residential census tract. I also observe the middle school at which they are enrolled, and their 7th grade standardized exam scores.

High school and program directories are publicly available online (New York City Department of Education 2022b). These directories contain several program characteristics, including the program name and interest area that I use to categorize programs into themes, and the admissions method. I supplement these program-level characteristics with additional public data on school-level demographics, outcomes, and report cards (New York City Department of Education 2022a; New York City Department of Education 2022c; New York City Department of Education 2022d).

I observe the rank-ordered application lists that each 8th grader in my sample submitted to the centralized high school assignment system for the main and supplementary rounds. I observe their first round and second round offers, final assignments, and final 9th grade enrollments. I observe enrollment at all New York City public high schools, including Exam / Audition schools, and excluding charter schools.

Finally, I observe high school outcomes, including attendance, test scores, graduation, and postsecondary outcomes.

My school choice model relies on computing public transit travel times between the centroid of each applicant's census tract, and each program in their choice set. I do so using OpenTripPlanner, an open source software built on publicly available street maps and timetables from public transit agencies (Appendix B).

My sample consists of 366,082 unique New York City 8th grade applicants to New York City public high schools from 2011-12 to 2017-18. I restrict the sample to applicants with nonmissing race indicator, poverty indicator, 7th grade test scores, and residential census tract. Since my study is motivated largely by racial segregation, and I present my results by a rich set of interactions of race, income and achievement, I restrict my sample to focus on the four racial groups that make up 99% of applicants: Black, Asian, Hispanic, and white.

The Department of Education splits the capacity of each program into General Education

School for Mathematics, Science and Engineering at City College of New York, High School of American Studies at Lehman College, Queens High School for the Sciences at York College, Staten Island Technical High School, and Stuyvesant High School.

(GE) and Students with Disabilities (SWD). I limit my sample to GE applicants (86% of applicants) because I am unable to replicate the assignment of SWD applicants via the DA mechanism with a high degree of accuracy, possibly due to more manual assignment for this group[6]. The assignment mechanism runs separately in parallel for both seat groups, so the removal of SWD applicants will not affect my ability to simulate the assignment of GE students.

The baseline patterns in application and enrollment with respect to theme and segregation in Section 4, reported for sample students only, change little when including SWD students. However, the model estimates, counterfactual simulation results, and theme enrollment effects should be interpreted keeping in mind that they do not necessarily represent students in the SWD applicant group.

Descriptive statistics for the full sample of high school applicants, the subsample who eventually enroll at a New York City high school, and the rates of various enrollment outcomes are in Table 2.

Over the time period of the study there are 935 unique programs in 465 schools. Table 1 shows how programs are distributed across theme, and Figure 1 shows how the themed programs are distributed throughout the city. The Humanities and Interdisciplinary theme connotes a general high school, and can alternatively be thought of as "unthemed".

4 Descriptive Evidence

4.1 General Application Descriptives

I begin by presenting an overview of what student applications look like. My sample includes 366,082 New York City public 8th grade applicants to New York City public high schools, from 2011-12 to 2017-18.

Their median application list length is 7, with over 80% ranking fewer than 12 programs. The median application has 3 distinct themes represented, and a theme concentration (proportion of ranked programs within the most-ranked theme) of 0.5. 46 % of students are assigned their first choice in the main round. 80% of students ultimately enroll in their main round match. 7% enroll at an Exam / Audition school, 3% are assigned to another New York City public high school through the supplementary or administrative round , 1% remain unassigned, and 8% received an assignment but did not enroll at a New York City non-charter public high school. Over 80 percent of programs reject at least one applicant who proposes in the mechanism, indicating that they are at capacity,

[6] Note that some students with disabilities apply to GE instead of SWD seats: these students make up 6% of my sample.

4.2 Application and Enrollment Behavior with Respect to Theme, by Demographic Group

Figure 2 shows differences in application and enrollment behavior by race, with respect to theme. Panels (a) and (b) plot differences in application behavior by race, with respect to theme. Panel (a) plots, by race, the proportion of applicants ranking each theme first. Panel (b) plots, by race, the proportion of applicants ranking each theme more than any other theme. Both application panels suggest that white (and to a lesser extent, Asian) applicants are more likely to rank Humanities and Interdisciplinary programs first, and frequently, than other groups. Black and Hispanic students, on the other hand, are more likely to rank the more specialized themes. These differences in ranking behavior are somewhat attenuated by enrollment decisions, as shown in panel (c). Panel (c) shows the themes at which students ultimately enroll. It also indicates whether applicants remain unassigned, are reassigned from their main round assignment, enroll at an Exam / Audition school, or Opt Out (do not enroll at a New York City public high school). This last option is indicated by the white space at the top of each bar. While white students are more likely to enroll at Humanities and Interdisciplinary programs than non-white students, the difference is smaller than it is for application.

Figures 3 and 4 show application and enrollment behavior by income and baseline achievement of applicants, rather than by race. Non-low-income students, and high-achieving students, are more likely to rank Humanities and Interdisciplinary programs, relative to more specialized themes. High-achievement students are also more likely to rank Science schools. However, much of the application gap by achievement with respect to Humanities and Interdisciplinary and Science goes away in enrollment. This suggests that the high-achieving students interested in Humanities and Interdisciplinary and Science schools are especially likely to be the ones in this group who end up at an Exam / Audition school, or Opt Out.

Table 3 presents mean school-level characteristics of each high school program, by theme. While high schools containing multicultural programs stand out as having smaller total enrollment, more English language learners, and more students with low test scores at baseline, for the most part, the differences in characteristics across theme are not large. Table 4 presents mean school-level graduation outcomes of each high school program. While Computing and Engineering stands out as enabling many students to graduate with a Career and Technical Education endorsement on their high school diploma, in general, differences in outcomes across theme are not large.

4.3 Segregation in New York City High Schools

Since I will eventually explore the extent to which themes contribute to segregation in the New York City public high schools, I provide descriptive evidence on the baseline level of segregation by race, income, and achievement[7]. To measure segregation, I use the variance ratio index of segregation, a widely-used measure of same-group isolation (Massey and Denton 1988). Let applicant i's same-

[7] Note that throughout this paper, segregation measures are computed as if sample students make up the entire high school applicant population.

group exposure in a school or city, $SGE_{i,school}$ or $SGE_{i,city}$, equal the proportion of high school applicants in the same race, income, or achievement group as i in i's school or city. Then, the school segregration index is defined as follows:

$$SI = \frac{1}{N}\sum_{i}^{N}\frac{SGE_{i,school} - SGE_{i,city}}{1 - SGE_{i,city}} \tag{1}$$

The numerator of the variance ratio equals the average deviation in same-group exposure experienced by applicant i at their school, from their same-group exposure in the city. It can be interpreted as the excess isolation of this group relative to a perfect integration benchmark. The denominator is the maximum excess same-group exposure, $1 - SGE_{i,city}$, that would even be possible in the reference population (the excess isolation in a complete segregation benchmark) (Monarrez et al. 2022). The adjustment makes it easier to compare the index values across subgroups with different levels of representation in the reference population.

The overall segregation index in Equation 1 can be computed by summing over all students, or a group-specific segregation index can be computed by summing over only the students in one racial, income, or achievement group.

I define my segregation index to use the reference population of same-cohort[8] 8th grade applicants. As a result, students who opt out of district public schools are part of the reference population, even when their same-group exposure is not captured in the index. If all schools in the city perfectly mirrored the demographics of 8th grade high school applicants in the city, the index would equal 0.

The segregation index for various residential subdivisions of New York City for each demographic subgroup of our sample students are in Table A1. The first column shows the proportion of the applicant sample in each race, income, and baseline achievement group.The other three columns provide a picture of residential segregation in New York City, with city demographics as the reference population. While boroughs are fairly representative of the population of New York City, there is more segregation across school subdistricts[9]. Census tracts are the most highly segregated; Table A2 shows lower segregation indices for schools and programs than census tracts, indicating that schools and programs are integrated relative to census tracts. Table A2 shows segregation across the main round assigned school, as well as segregation across actual schools enrolled, which takes into account changes in school enrollment occurring through the supplementary round and specialized high school enrollment process, as well as students exiting the district. The segregation indices are reported by race, income, and achievement. These values can be interpreted as an individual in each group's mean experience of racial isolation in their school or program, as it reflects the distance between their same-group exposure at their school or program and same-group exposure in their city.

[8] Year subscripts are omitted from 1 for simplicity, but all exposure measures are computed within-cohort.

[9] The New York City school system is broken up into 32 districts. I refer to these "districts" throughout the paper as "subdistricts" to distinguish them from the whole New York City school "district", which I use to refer to the entire school system.

5 Model

In previous section, I have provided descriptive evidence on differences in application and enrollment behavior with respect to themed schools by race, income, and achievement. I now attempt to quantify the extent to which theme preferences drive school choice, relative to other school characteristics. To do so, I estimate a structural model of high school choice that allows for strategic behavior (Agarwal and Somaini 2018; Idoux 2021).

5.1 Definitions

There are N applicants $i \in \{1, ..., N\}$ to New York City high schools during the years $t \in \{1, ..., T\}$. There are J programs indexed $j \in \{1, ..., J\}$ that are available in at least one year in this time period. Each student has a program choice set $CS(i) \subset J$. Let $\mathcal{CS}_i$ equal the set containing all ordered subsets of CS_i from size 1-12, which is i's application choice set. Each student i submits a rank-ordered list $R_i \in \mathcal{CS}_i$.

For all students, the choice set includes the outside option 0. This option represents enrolling in an assignment from the supplementary or administrative round of the match, enrolling at an Exam / Audition school, attending a charter school, attending a private school, or attending a public school outside of New York City. Note that students are free to pick the outside option whether or not they receive an assignment from the main round of the match.

5.2 Subjective Assignment Probabilities

When applicants add programs to their list, they take into account their subjective probability of assignment to each program. They do not add a program to their list if their expected utility from that program (the indirect utility of that program weighted by assignment probability) is less than their marginal application cost. In this section, I explain my model and estimation of applicant beliefs.

5.2.1 Assignment probabilities

I model applicant beliefs as consistent with the equilibrium outcome. The probability that applicant i is assigned to program j if they rank it in slot k is $p_{ijk}(R_{i,k-1}, \mathbf{q_i})$. $R_{i,k-1}$ refers to the programs that applicant i ranked in slots 1 through $k-1$ of their list. Note that applicant i cannot be assigned to a program they rank in slot k without being rejected from the programs they rank in slots 1 through $k-1$. $\mathbf{q_i} := (q_{i1}, ...q_{iJ})$ is the full vector of subjective probabilities q_{ij} that applicant i will be admitted to program j. In the context of the centralized assignment mechanism, where each applicant only gets one offer from the assignment mechanism, i's "admission" to j refers to whether i's lottery tiebreaker clears j's priority and lottery cutoff, if j is a lottery program, or i's score clears j's priority and score cutoff, if j is a score program. I describe below how $\mathbf{q_i}$ is computed to be consistent with the equilibrium outcome, conditional on applicant i's information set.

For applicant i ranking program j in slot k, the true assignment probability $p_{ijk}(R_i)$ is their probability of being rejected at programs they rank in slots 1 through $k-1$, and assigned to program j. Note that each applicant is assigned a single lottery tiebreaker that is used for them at any lottery they enter over the course of the iterations of the Deferred Acceptance algorithm. For this reason, admissions at lottery programs are dependent events. The formulas for computing assignment probabilities as a function of ranked list and subjective admit probabilities take these dependencies into account (Appendix C).

5.2.2 Model of coarse beliefs

I model applicant beliefs as consistent with the equilibrium outcome, but coarse. For applicant i and program j, let $priority_{ij}$ be i's priority at j, $rank_{ij}$ be i's rank at j, if j is a score program, and $tiebreaker_i$ be i's lottery tiebreaker. Applicant i's admission at program j is a function of these three variables. I allow applicant i to know $priority_{ij}$, but not the other two variables. Instead of their exact rank, $rank_{ij}$, applicant i only knows $rankcat_{ij}$ a coarser category based on their characteristics [10]. $rankcat_{ij}$ is uninformative for lottery programs, so I set it to 0 if j is a lottery program. Then, applicant i's information set is $\mathbf{\Omega_i} = ((priority_{i1}, rankcat_{i1}), ..., (priority_{iJ}, rankcat_{iJ}))$. The information set reflects what an applicant would know in reality: rules for individual priority can be determined from a program's directory entry, but applicants would not know their exact rank at a score program or the tiebreaker that will be drawn for them at lottery programs.

One small deviation from consistent beliefs is that I do not allow perceived assignment probability to be 0 or 1. I truncate perceived assignment probabilities p_{ijk} to be within $[.01, .99]$. I do this to rationalize, given positive marginal application costs, applicant decisions to rank programs that they do not have a chance of getting into in equilibrium, and to continue adding programs to their list even if their probability of rejection from all higher-ranked programs is zero in equilibrium.

5.2.3 Admit probabilities

As described above, the assignment probabilities p_{ijk} depend on applicant i's choice of R_{k-1} and vector of admit probabilities, $\mathbf{q_i}$. In this section, I discuss how I assign subjective admit probabilities q_{ij} to all applicants i for all programs j in their choice sets. The assigned admit probabilities q_{ij} are consistent with the equilibrium assignment, conditional on i's information set $\mathbf{\Omega_i}$.

Let q_{ij} equal the subjective probability i is admitted to j. The marginal priority for program j refers to the priority group within which the lottery or score determines admission. For any program j, q_{ij} equals 1 if $priority_{ij}$ is above than the marginal priority for j, 0 if $priority_{ij}$ is below than the marginal priority for j, and the frequency at which applicants with characteristics $\mathbf{\Omega_i}$ are admitted to j if $priority_{ij}$ is the marginal priority for j. In the Deferred Acceptance mechanism, q_{ij} does not depend on the slot in which i ranks j.

[10] For screened programs, the rank category is based on baseline achievement category. For audition programs, the rank category is based on application and admission to an Audition program.

The uncertainty around admission arises from the fact that the applicant does not know their lottery number (for a lottery program) or exact relative rank (for a score or audition program) within rank category [11].

5.3 Application Cost

Since the vast majority of applicants do not fill out all of their rank slots, I include application costs in my model. Without application costs, I would need to assume that these students prefer or are indifferent between the outside option and the programs they do not rank. If this assumption is untrue, and some of the unranked programs are very similar to ranked programs on observables, estimating a model with application costs would inflate the taste shock variance relative to the other coefficient estimates.

Application cost is parameterized as linear in application length. Applicant i's marginal application cost c_i is distributed $TruncatedNormal(0, \infty, c, \sigma_\zeta)$.

5.4 Model of Application Choice

An individual's application R_i induces a lottery over assignments to each program they list. Agarwal and Somaini (2018) models application choice as the choice of the optimal lottery. In my setting, the number of possible applications for each applicant is intractable. Even limiting each applicant's choice set to $|CS(i)| = 30$ programs, each applicant chooses among $\sum_{i=0}^{11} \frac{30!}{(12-i)!}$ application portfolios. Estimation of a model in which applicants choose among all portfolios would involve repeatedly computing the expected utility of all of these portfolios for all applicants, which is not feasible.

Following Idoux (2021), I simplify the problem by assuming the applicants use a heuristic to form their lists. They sequentially pick the highest utility program in their consideration set, declining to consider programs with low assignment probability as they move down their list. The heuristic is consistent with the DOE's advice to student to list programs in order of preference, but include a combination of low- and high-demand programs [12]. This heuristic follows from an assumption of Limited Rationality:

Assumption 1. *(Limited Rationality of Applicants, Assumption 1 in Idoux (2021)).*
v_{ij} is the utility applicant i receives from being assigned to program j. p_{ijk} is the probability i is assigned to j. c_i is the per-unit cost of application for applicant i. $R_{i,k-1}$ refers to the order-preserving subset of R_i containing the first $k-1$ elements of R_i. Program $j = 0$ represents the outside option.

[11] My approach differs from the rational expectations baseline in Agarwal and Somaini (2018), in which the applicant knows her rank within the population distribution of applicants, but uncertainty arises instead the from the applicant pool changing year-to-year.

[12] https://www.schools.nyc.gov/enrollment/enroll-grade-by-grade/high-school

For each position k in the list, an applicant i chooses $j \in \{0\} \cup \{1, ..., J\} \setminus R_{i,k-1}$ to maximize:

$$v_{ij} p_{ijk}(R_{i,k-1}) - I(j \neq 0)c_i + \tilde{V}_k(\{j\}) \tag{2}$$

where the continuation value for position k is defined for each ordered set of choices C as:

$$\tilde{V}_k(C) := \max_{j' \in \{0\} \cup \{S_k \setminus C\}} v_{ij'} p_{ij',k+|C|}(R_{i,k-1} \cup C) + \tilde{V}_k(C \cup \{j'\}) \tag{3}$$

where $S_k = \{j' \in \{0\} \cup \{1, ..., J\} \setminus R_{i,k-1} : v_{ij'} p_{ij'k}(R_{i,k-1}) - I(j' \neq 0)c_i \geq 0\}$ i.e. S_k is the "consideration set" consisting of remaining programs which would clear the per-unit cost c_i if they were added in position k.

The applicant maximizes this objective function sequentially by picking the highest utility program in her consideration set, step by step, until $\{0\}$, the outside option, is the only element left in the consideration set. The applicant's "mistake" is in the specification of her continuation value, in which the consideration set is the same as it is in the current step. The applicant acts as if her consideration set will not change in future steps.

This strategy deviates from full rationality when ranking a different program at k instead would increase the expected utility of the application, but the other program never gets ranked because after rank k, it is no longer part of the consideration set. The limited rationality applicant does not consider this; she acts as if she will eventually rank every program in her current consideration set, not anticipating how the consideration set will evolve further down the list. There is no reason for her to consider ranking a non-maximum utility program, because she believes she can rank it later without hurting her conditional probability of assignment, thanks to the properties of Deferred Acceptance.

Under full rationality, the continuation value is correctly specified, so the applicant would choose a non-maximum-utility program at spot k , if doing so would increase the total expected utility of the application.

5.5 Parametrization of Indirect Utility

The indirect utility for applicant i of assignment to program j is v_{ij}.

$$v_{ij} := \delta_{cell(i),j} + \theta_{boro(i),boro(j)} + \mathbf{X_{ij,t(i)-1}} \boldsymbol{\beta_{cell(i)}} - d_{ij} + \gamma_{cell(i),ms(i),t(i),theme(j)} + \epsilon_{ij} \tag{4}$$

$$v_{i0} = \epsilon_{i0} \tag{5}$$

$\delta_{cell(i),j}$ is a demographic cell-by-program fixed effect. $\theta_{boro(i),boro(j)}$ is a residential borough-by-program borough fixed effect. $\mathbf{X_{ij,t(i)-1}}$ includes time-varying program characteristics (lagged proportion of assigned students who are high-achieving, lagged proportion of assigned students who are same-race). d_{ij} is the public transit travel time between i's census tract and j's location. $\gamma_{\mathbf{cell(i),ms(i),t(i)}}$ is a random vector of unobserved preference for each theme at the demographic group, middle school cohort level, distributed $MultivariateNormal(\mathbf{0}, \mathbf{\Sigma}_\gamma)$. This term captures correlation of preferences with respect to theme within same demographic cell, middle school cohort, which would pick up similar application behavior with respect to themes due to applicants wanting to go to the same high school as their middle school friends, or applicants receiving similar advice from their middle school guidance counselor. I allow these unobserved preferences to be correlated across themes; a positive covariance in Σ_γ tells us that groups of same demographic, same middle school cohort students that prefer one theme prefer the other as well.

ϵ_{ij} is a taste shock, distributed $Normal(0, \sigma_\epsilon)$. I set the coefficient on travel time to -1 as a scale normalization, and the expected indirect utility of the outside option to 0 as the location normalization. The unit of travel time is 1000 seconds, which is approximately 15 minutes. Therefore, the scale of coefficient estimates can be interpreted in relation to the disutility from 15 additional minutes of public transit travel time. The location normalization means that all v_{ij}s can be interpreted as an individual's value of a program relative to their value of being unassigned after the main application round.

5.6 Identifying Theme Preference

So far, I have not mentioned how theme preferences enter the model. In the parametrization of indirect utility, theme preferences are absorbed by the program-by-year fixed effect. If we wanted to examine how preferences over programs of each theme differ, on average, we could compare the average program-by-year FE for each theme, by demographic group of interest.

However, this comparison would not allow us to disentangle theme preference from preference over other time-invariant program characteristics. Thus, I implement a second step after estimation of the structural model. I regress program-by-year fixed effects $\delta_{cell(i),j}$ on non-Humanities and Interdisciplinary theme-by-demographic cell dummies, time-invariant program characteristics $\mathbf{X_j}$, and demographic cell dummies.

$$\delta_{cell,j} = \alpha_{cell,theme(j)} + \boldsymbol{\eta}\mathbf{X_j} + \rho_{cell} + \upsilon_{cell,j} \tag{6}$$

The coefficients on theme-by-cell dummies, $\alpha_{cell,theme}$, capture each demographic cell's preference for programs of each theme, on average, after controlling for time-invariant program characteristics, relative to the their preference for Humanities and Interdisciplinary programs.

While estimating $\alpha_{cell(i)}$ is necessary for implementing the counterfactual, and for learning about preferences over all themes, I also estimate an alternative specification aimed at learning how much applicants like any themed program on average, relative to Humanities and Interdisciplinary. I regress program-by-year fixed effects on a dummy for non-Humanities and Interdisciplinary.

$$\delta_{cell,j} = \phi_{cell}[theme(j) \neq Hum.] + \boldsymbol{\eta}\mathbf{X_j} + \rho_{cell} + \xi_{cell,j} \tag{7}$$

The non-humanities coefficients, ϕ_{cell}, capture each demographic cell's preference for themed programs, on average, after controlling for time-invariant program characteristics, relative to the their preference for Humanities and Interdisciplinary programs.

I include a rich set of time-invariant program and school characteristics in $\mathbf{X_j}$, so that $\alpha_{cell,theme}$ and ϕ_{cell} credibly capture theme preference, rather than other program characteristics. These contains school size, 4-year school graduation rate, school leadership effectiveness rating based on parent and teacher survey responses, and proportion low-income in program (all measured in the first year the program was observed in the data). Note that I do not want $\mathbf{X_j}$ to contain characteristics that are inextricably linked with theme, since I want to be able to identify preferences over theme. For example, I do not necessarily want to control for availability of Career and Technical Education or language courses, I consider these to be part of how themes are implemented, and want them to be reflected in the theme coefficients.

6 Identification

In settings with strategic reporting of preferences, Agarwal and Somaini (2018) details the conditions for non-parametric identification of the distribution of indirect utilities. One sufficient condition is the existence of a "special regressor", which is additively separable in the indirect utility function and independent of the unobservable component of utility . In my setting, travel time serves this role, requiring the assumption that conditional on observed student and program characteristics, the unobservable components of utility $(\epsilon_{ij}, \gamma_{\mathbf{cell(i),ms(i),t(i)}})$ are independent of travel time. If students systematically tend to live near programs they prefer, after controlling for observables, my estimates would understate preferences for other characteristics relative to travel time. Note that the inclusion of residential borough-by-program borough fixed effects means that only within-borough correlation of travel time and unobserved preference is a threat to identification. The distribution of indirect utilities is nonparametrically identified by variation in travel time within student demographic group and program characteristics.

The distribution of marginal application cost is identified by cross-sectional and cross-year variation in admission probabilities (Idoux 2021). Costs are identified by the degree of response in ranking behavior to shifts in admission probabilities. Applicants who want to respond to a downward shift in assignment probabilities by ranking more programs may be inhibited from doing so by their marginal application costs.

The theme correlation term is identified by within-same demographic cell, middle school cohort ranking behavior with respect to each pair of themes, that is, whether a demographic cell-by-middle school cohort group that ranks a lot of one theme is likely to rank a lot of the other theme.

7 Estimation

I compute program assignment probabilities in equilibrium, and set each applicant's subjective program assignment probabilities to these. Then, I estimate the choice model. Finally, I decompose the estimated demographic cell-by-program fixed effects to estimate theme preference by demographic cell.

7.1 Subjective Probabilities of Assignment

The assignment probabilities p_{ijk} depend on the admit probabilities q_{ij}, so I compute those first. Following the assumption of consistent beliefs, I set q_{ij} equal to the proportion of applicants in priority group $priority_{ij}$ and rank category $rankcat_{ij}$ who clear the priority cutoff or are marginal priority and clear the score cutoff, for a score program, and clear the marginal priority or are marginal priority and clear the lottery cutoff, for a lottery program. One challenge is that I do not observe i's priority or rank at j in the data if i did not apply to j. Thus, I back out the rules for assigning priority from the characteristics and assigned priorities of applicants to each program, and use these to impute the priorities for non-applicants.

I compute the probability of assignment for each applicant i to each program j in slot k, which is a function of $\mathbf{q_i}$ and choice of higher-ranked programs $R_{i,k-1}$. p_{ijk} equals the probability of being rejected from all programs in $R_{i,k-1}$, and admitted to program j. Appendix C contains the formulas for computing assignment probabilities from admit probabilities in a way that accounts for interdependencies in admission events.

7.2 Choice Model

Since there is no closed-form solution for the likelihood function, and large choice sets raise challenges of simulation error and tractability with simulated maximum likelihood, I follow the previous literature and instead use a Gibbs sampler adapted from McCulloch, Rossi, and Allenby (1996) to estimate my model (Abdulkadiroglu, Agarwal, and Pathak 2017; Agarwal and Somaini 2018; Idoux 2021).

The Gibbs sampler yields estimates asymptotically equivalent to the maximum likelihood estimator. The mean of the posterior distribution of the parameters, given the prior distribution and the data, is asymptotically equivalent to the maximum of the likelihood function. The posterior distribution is simulated by repeatedly taking draws from the posterior one parameter at a time, conditional on the values of the other parameters. After enough iterations, the sampler converges to draws from the joint posterior of all of the parameters. The means of the parameter draws post-convergence are their point estimates, and the standard deviations are their standard errors.

Because of the bounds on indirect utilities and costs (Appendix D) derived in Idoux (2021) as a result of Assumption 1, the number of constraints on utilities is linear rather than exponential in program choice set size. Further estimation details are in Appendix E.

7.3 Identifying Cell-by-Theme Preference from Cell-by-Program Fixed Effects

I store the cell-by-program fixed effects draws $\delta_{cell(i),j}$ for each iteration of the Gibbs sampler. Post-estimation, for each post-convergence iteration, I run the regression specifications in equations 6 and 7. I get point estimates and standard errors from the coefficients from each iteration by taking the mean and standard deviation over iterations, respectively.

8 Results

8.1 Preference for Themed Schools, Relative to Humanities and Interdisciplinary

Figure 5 plots 95 % confidence intervals for the theme preference coefficients, $\phi_{cell(i)}$. These coefficients represent the mean preference for the themed programs, relative to Humanities and Interdisciplinary programs, for each demographic cell. All of the point estimates are negative and significant, indicating that all subgroups prefer Humanities and Interdisciplinary themed programs to the other themes, on average.

Preferences vary by race. Consistent with the descriptive evidence on application behavior, white and Asian applicants have higher relative preferences for Humanities and Interdisciplinary programs than Black and Hispanic applicants.

In general, keeping other demographic characteristics fixed, low-income and non-high baseline achievement applicants have stronger relative preferences for themed programs, compared to non-low-income and high baseline achievement applicants, respectively. While differences across income and achievement generally appear lower in magnitude than those across race, they appear to be an especially important driver of theme preference heterogeneity within Black and Asian applicants.

Figure 6 plots 95 % confidence intervals for theme preference, relative to Humanities and Interdisciplinary and Science, rather than just Humanities and Interdisciplinary. Again, on average, White and Asian applicants have higher relative preferences on for Humanities and Interdisciplinary and Science programs than Black and Hispanic applicants. Compared to the coefficients relative to just Humanities and Interdisciplinary, I observe clearer patterns of heterogeneity by achievement, consistent with descriptive evidence on application and enrollment. High-achievement applicants have stronger preferences for Humanities and Interdisciplinary and Science programs than non-high achievement applicants; the difference in preference between high- and low-achievement applicants is significant within every race-by-income group.

Both Figures 5 and 6 mask considerable heterogeneity of preferences over the nine themes. Table A4 contains estimates for the entirety of relative theme preference coefficients, $\alpha_{cell,theme}$. Table 5 displays the top three preferred themes for each demographic cell. It provides an idea of the extent of theme preference heterogeneity across demographic groups.

8.2 Other Parameter Estimates

Table A3 displays estimates of taste shock variance, mean marginal application cost, and application cost variance. I estimate a taste shock variance of 7.33, which is quite large relative to other coefficient estimates, indicating substantial unobserved heterogeneity in preferences. Magnitude-wise, this estimate is in line with other estimates of this parameter in school choice models (Abdulkadiroglu, Agarwal, et al. 2017; Idoux 2021). For the marginal cost distribution, I estimate a mean of 0.0089 and a variance of 0.00004.

My estimates for within-middle-school-cohort-cell correlation of unobserved theme preferences are in Table A5. One notable result that unobserved preferences for Military and Law Enforcement programs, within students in the same demographic group, middle school, and cohort, are highly correlated, with a covariance of 20.05, indicating that even after controlling for mean preferences by observable characteristics, some groups of applicants strongly like these programs, and some strongly dislike them. Unobserved preferences for Military and Law Enforcement programs and Multicultural programs, are also in general negatively correlated with unobserved preferences for other themes, indicating that applicants who like these themes tend to only like these themes, and dislike other themes. Finally, unobserved preferences for Humanities and Interdisciplinary programs and Science programs are positively correlated.

9 Counterfactual

I use the model estimates to simulate the counterfactual assignment of students that would occur if programs were not differentiated by theme (that is, if all programs were Humanities and Interdisciplinary). By comparing measures of segregation by race, income, and achievement in this counterfactual regime to those in the status quo regime, I capture the contribution of theme preference to segregation in the status quo.

From my estimates, I compute program indirect utility relative to the outside option, both in the baseline and the counterfactual simulation. I model the decision to exit the New York City public school district as a probit of demographic cell, assigned program utility, Exam school offer, and Audition school offer. I predict whether each applicant exits the district in the simulations.

9.1 Simulation

For a variety of reasons, I cannot perfectly replicate the assignment process that would be used by the New York City Department of Education for a counterfactual set of applications [13]. Therefore, I compare the results of my counterfactual simulation to the results of my baseline simulation, rather than the real data. That way, the difference between the two is not driven by simulation error.

I take the following steps to simulate the baseline and counterfactual assignments.

[13] One reason is that I do not observe program ranks or priorities for applicants at a program unless they actually applied to it.

1. I set model parameters equal to their point estimates.

2. For the counterfactual, I set the theme preference coefficient $\alpha_{cell,theme}$ to 0 for all themes, updating the program-by-cell fixed effects $\delta_{cell,theme}$ accordingly. Since $\alpha_{cell,theme}$ was estimated relative to Humanities and Interdisciplinary, 0 is the coefficient for Humanities and Interdisciplinary. For the baseline, I keep $\delta_{cell,theme}$ the same.

3. I compute the non-random component of indirect utility for each program in each applicant's choice set.

4. For K iterations:

   a) Get random variable draws. Use the draw of random variable values ϵ_{ij}, $\gamma_{cell(i),ms(i),t(i),theme(j)}$, and v_{ij} from one iteration of the Gibbs sampler. For the counterfactual, I set $\gamma_{cell(i),ms(i),t(i),theme(j)}$ to $\gamma_{cell(i),ms(i),t(i),\text{Humanities and Interdisciplinary}}$. Using draws from the Gibbs sampler incorporates additional information from the data about likely values for these variables.

   b) Compute indirect utilities for each program in each applicant's choice set.

   c) Until a fixed point is reached:

      i. Compute assignment probabilities for each program in each applicant's choice set, using the formulas in C.

      ii. Given the assignment probabilities to each program and utilities, select applications for each student according to their objective function 1

      iii. Given student applications, run the Deferred Acceptance algorithm to get the updated program assignments. Since I do not observe $rank_{ij}$ I impute rank as $rankcat_{ij}$ with ties broken randomly for Audition programs, and 8th grade math and ela scores for other programs.

      iv. Compute admit probabilities consistent with the new assignments.

      v. Update last year's program assignee characteristics to be consistent with the new applications.

      vi. Update program utilities to reflect the updated last year assignee characteristics for each program's school.

   d) Estimate a probit model of district exit using the real data, as a function of demographic cell, Exam / Audition school offer, and indirect utility of the main round assignment, for students assigned in the main round. Repeat for students unassigned in the main round, with the model depending only on demographic cell and Exam / Audition school offer. Use the estimated probit model to predict who will exit the district in the baseline and counterfactual simulations, using their simulated main round outcomes. If I predict a student stays in the district, and I observe them enrolling at an Exam / Audition school and program in the real data, I assume they enroll at the same Exam / Audition school and program in the counterfactual. If I predict an unassigned student stays in the district, and I observe them enrolling at any school and program in the real data, I assume they enroll at the same school and program in the counterfactual.

e) Compute segregation indices, district exit rates, and other parameters of interest based on the simulated assignments, and simulated enrollments post-district exit.

5. Using the mean and standard deviation over all iterations, report point estimates and standard errors for segregation indices, district exit rates, and other parameters of interest.

9.2 Results

I present results of comparing the simulated Humanities and Interdisciplinary-only counterfactual to the simulated baseline. My main comparison parameters of interest are the segregation indices, district exit rates, and assigned program utilities. Appendix F discusses general changes in application patterns from the baseline to the counterfactual, which helps explain the mechanisms behind some of the changes in parameters I care about.

9.2.1 Segregation and district exit

Figure 9 plots district exit rates for each demographic subgroup in the model estimation sample. Relative to the baseline with themes, white and non-low-income applicants in the all-Humanities and Interdisciplinary counterfactual see a slight reduction in district exit. While this comparison is consistent with curricular differentiation contributing to white flight, the decreases are not statistically significant. None of the differences for any group are statistically significant, suggesting that curricular differentiation does not drive exit decisions.

Figure 10 compares the segregation indices in the counterfactual simulation to the baseline simulation. The first figure compares simulated baseline and simulated counterfactual segregation indices of program assignment. The second figure compares the simulated baseline and simulated counterfactual segregation indices of program enrollment. I find that relative to the baseline, the all-Humanities and Interdisciplinary counterfactual regime modestly decreases segregation by race. The differences are small, but significant. I find even smaller decreases in segregation by income and achievement, but they are not significant after accounting for enrollment decisions (except for low-income students). Enrollment decisions appear to mitigate the contribution of curricular differentiation to segregation, as seen by the smaller baseline to counterfactual gaps when considering enrolled versus assigned high school program. One possible explanation is that the applicants most likely to exit are especially likely to have been assigned to programs where they would have experience high same-group exposure. Overall, the results suggest that curricular differentiation increases racial segregation by an extremely small magnitude relative to existing levels.

9.2.2 Welfare

Figure 7 presents the change in mean assigned program utility, from the baseline to the counterfactual simulation. Except for Black applicants, who on average have relatively strong preferences for themed programs relative to Humanities and Interdisciplinary, all demographic groups are better off, with substantial heterogeneity in magnitude. Non-low-income white and Asian applicants benefit the most. The results are driven by applicants within those demographic subgroups who, due to supply constraints, were assigned to non-Humanities and Interdisciplinary programs in the baseline in spite of strong relative preferences for Humanities and Interdisciplinary schools.

Not all applicants are better in the Humanities and Interdisciplinary-only counterfactual, even within demographic groups who are better off on average (Figure 8). Over half of low-income Black students are worse off in the counterfactual. Substantial minorities of other demographic groups are also worse off in the counterfactual. This finding highlights the importance of unobserved preference heterogeneity in this setting; and is consistent with the relatively large magnitudes of σ_ϵ and Σ_γ. It also suggests that increasing the capacity of Humanities and Interdisciplinary seats, while preserving specialized program seats, would leave more students better off than replacing all specialized program seats with Humanities and Interdisciplinary.

The mean utility changes in Figure 7 can be converted to minutes of travel time. From the scale normalization, one unit of utility is worth 1000 seconds of travel time. White, non-low income, non-high baseline achievement students are better off by 4.6 minutes of travel time on average in the all-Humanities and Interdisciplinary counterfactual. Black, low income, non-high baseline achievement students are worse off by 3.4 minutes of travel time.

Note that these welfare changes are driven both by applicants who enroll at a different program in the counterfactual and those who stay at the same program. Applicants who enroll at the same program in the simulated counterfactual may have a different enrollment utility, because the program in the counterfactual is now a Humanities and Interdisciplinary program instead of its baseline theme.

10 Causal Impacts of Enrollment at Each Theme

So far, I have focused on the implications of themes for student sorting across schools. In this section, I shift my focus to the implications of themes for educational outcomes, estimating the causal effect of enrollment at each type of program. To answer whether students benefit from enrolling at programs that align with their curricular interests, I also estimate the theme effects interacted with whether the theme is the student's favorite theme. This analysis provides evidence on the potential of themed programs to improve match quality by increasing alignment between student interest and curriculum. A positive interaction effect indicates that students' theme preferences encourage them to sort positively into programs on expected gains, increasing the efficiency of education production.

10.1 Individual Theme Preference

In order to determine whether students benefit from being assigned to themes they prefer, relative to others, I first estimate individual theme preference coefficients. The individual theme preference coefficients $\chi_{i,theme}$ for each applicant i are:

$$\chi_{i,theme} = \alpha_{cell(i),theme} + \gamma_{cell(i),ms(i),t(i),theme} + \bar{\epsilon}_{i,theme} \tag{8}$$

$\alpha_{cell(i),theme}$ is the demographic cell-level component of theme preference. $\gamma_{cell(i),ms(i),t(i),theme}$ is the cell by middle school cohort-level component of theme preference. And finally, $\bar{\epsilon}_{i,theme}$ refers to the average taste shock for programs of theme *theme* in i's choice set.

I obtain estimates of $\chi_{i,theme}$ for each applicant by taking its average value over the post-convergence Gibbs sampler draws.

10.2 Empirical Strategy

I use the lottery and score cutoffs embedded in the DA assignment mechanism to identify theme enrollment effects (Bloom and Unterman 2014; Abdulkadiroglu, Angrist, Narita, and Pathak 2017; Abdulkadiroglu, Angrist, Narita, and Pathak 2022). Conditional on preferences and priorities, the assignments resulting from lottery tiebreakers are "randomly assigned and therefore independent of potential outcomes" (Abdulkadiroglu, Angrist, et al. 2017). The same can be said of assignments in the neighborhood of a score cutoff, as we can assume score tiebreakers are locally uniformly distributed. Abdulkadiroglu, Angrist, et al. (2022) show how to estimate local DA propensity scores, which capture applicant preferences and priorities but have a much coarser distribution than the full distribution of applicant preferences and priorities, and use them to estimate enrollment effects. I run the following multi-sector 2SLS specification (Abdulkadiroglu, Angrist, et al. 2022):

$$\text{First Stage: } D_{theme,i} = \sum_{theme \in \mathcal{T}} \delta_{theme} Z_{theme,i} + \sum_{theme \in \mathcal{T}} \phi_{p(i,theme)} + \alpha \mathbf{X_i} + \nu_i \tag{9}$$

$$\text{Second Stage: } Y_i = \sum_{theme \in \mathcal{T}} \beta_{theme} D_{theme,i} + \sum_{theme \in \mathcal{T}} \xi_{p(i,theme)} + \omega \mathbf{X_i} + \epsilon_i \tag{10}$$

$Z_{theme,i}$ refers to whether student i is assigned to theme $theme \in \mathcal{T}$. $\mathcal{T}$ includes all specialized themes; effects are estimated relative to enrollment at a Humanities and Interdisciplinary or Exam/Audition school. $D_{theme,i}$ refers to whether a student ultimately enrolls in a program of theme *theme* as a freshman in the year following their application. Y_i is the outcome variable; outcomes include attendance rate in first year of high school, SAT-taking, graduation in 4 years, and postsecondary enrollment at various types of institutions in the fall after expected on-time graduation. $p(i, theme)$ is applicant i's local DA propensity score for theme *theme*; we include fixed effects $\phi_{p(i,theme)}$ and $\xi_{p(i,theme)}$ for all values of the scores observed in the sample. $\mathbf{X}_i$ is a vector of application and running variable controls. It includes, for each program, an indicator of application, an indicator of application and score program and in bandwidth, an indicator of application and score program and in bandwidth interacted with the score, and an indicator of application and score program and in bandwidth and above cutoff interacted with the score. I compute optimal bandwidths for 4-year graduation for each program following Calonico, Cattaneo, and Titiunik (2014), which I use for all outcomes [14].

There are 267,811 applicants in our sample from 2011-2016[15]. The theme effect estimation sample includes only students with non-degenerate risk for one of the specialized themes, as there is no variation in assignment within applicant groups that have a local DA propensity score of 1 for one of the themes. Excluding these students results in a sample of 83,582 students.

This model relies on the assumption that each sector has a constant effect across students. I interpret β_{theme} as the effect of enrollment at a program with theme *theme*, relative to enrollment at Humanities and Interdisciplinary or a Exam / Audition school.

I also investigate whether students who prefer a theme benefit more from enrollment at this theme than students who prefer a different theme[16]. I estimate a modified version of equation 9, in which I fully interact $Z_{theme,i}$ and $D_{theme,i}$ with an indicator of theme *theme* being applicant *i*'s favorite theme (the theme with the highest value of $\chi_{i,theme}$).

One threat to identification is that assignment could impact whether I observe outcomes. For example, if assignment to one particular theme affects whether a student enrolls in a New York City non-charter public high school at all, or their likelihood of switching out of the system during their time in high school, the treatment and control groups could be differentially selected on observable or unobservable characteristics once I restrict to applicants whose outcomes I oberve. I do not observe high school outcomes for 1.6 percent and postsecondary outcomes for 6.5 percent of the effect estimation sample. To address this concern, I test for differential sample attrition by treatment status, by running the first stage in Equation 9 with an indicator of missing outcome as the outcome. I also check whether the treatment and control samples for each subgroup of interest are balanced on several characteristics of interest, including gender, poverty status, race, and receipt of an Exam school offer.

Note that these theme enrollment effects should be interpreted as the effect of enrolling in a program of a particular theme, relative to a Humanities and Interdisciplinary program or Exam / Audition school. I do not investigate whether the theme itself is what drives the effects, but whether the programs in that theme differ in effect from programs in other themes.

10.3 Results

I estimate the effect of enrolling in each theme, relative to enrolling in Humanities and Interdisciplinary or an Exam / Audition school, on attendance rate in the first year, taking the SAT,

[14] In the future I will compute bandwidths for every outcome and use the smallest bandwidth for all outcomes.

[15] I exclude applicants from 2017, as I do not have all outcomes for them.

[16] Note: it is possible that their preference for the theme reflects the expected benefit of the theme to these outcomes. The theme preference estimates should be interpreted as a combination of utility from theme and utility from expected benefit to outcomes.

graduation within four years, and enrollment at various types of postsecondary institutions in the fall after on-time graduation. Figure 11 displays point estimates and 95% confidence intervals of the theme effects for each outcome. It also displays the p-value from the F-test for joint significance of the theme assignment effects. For every high school outcome, I reject the null hypothesis that the vector of theme assignments does not have predictive power for the outcome at the 5% level.

The results suggest that theme matters for high school outcomes. Arts and Design, Computing and Engineering, and Media enrollment have positive impacts significant at the 5% level on the most immediate outcome, attendance rate in the first year of high school. This initial effect does not seem to translate into gains in future high school outcomes. Business, Hospitality, and Services ($p < 0.10$), Media ($p < 0.01$), and Public Service, Law and Social Justice ($p < 0.01$) programs decrease applicants' likelihood of ever taking the SAT; Media ($p < 0.01$) and Public Service, Law, and Social Justice ($p < 0.10$) also decrease applicants' likelihood of graduating high school in 4 years.

I find that theme matters for whether students enroll in a in-state public 4-year institution (CUNY 4-year or SUNY)[17] by the fall after their expected on-time high school graduation. Computing and Engineering enrollment decreases the chance of enrollment at an in-state public 4-year institution ($p < 0.01$). This theme, which features high participation in Career and Technical Education, may induce students to pursue employment right after high school instead. At the 10% significance level, Public Service, Law and Social Justice and Science programs also decrease the likelihood of enrollment at in-state public 4-year institutions. I do not find evidence that theme affects enrollment at an in-state public 2-year institution (CUNY 2-year)[18], or at out-of-state or private institutions, right after expected high school graduation.

I also estimate a version of Equation 9 in which I fully interact $Z_{theme,i}$ and $D_{theme,i}$ with an indicator of theme *theme* being applicant i's favorite theme (the theme with the highest value of $\chi_{i,theme}$). I conduct an F-test of joint significance on all of the coefficients on the interaction terms. Under each plot in Figure 11, I display the p-value from this F-test. For all outcomes, I fail to reject the null at the 10% level that all interaction effects equal 0. Given that I find no evidence of effect heterogeneity by theme preference, I conclude that in this setting, any sorting into programs induced by theme preference does not increase efficiency.

Figures A4 and A5 show whether theme assignment affects missingness of high school outcomes and postsecondary outcomes, respectively. Multiple theme assignments appear to decrease the likelihood of missing high school outcomes, relative to Humanities and Interdisciplinary assignment.

[17] This category of enrollment includes all in-state public 4-year institutions in New York State. It also includes SUNY 2-year institutions, but I expect enrollment at these institutions to be minimal in this context since New York City recent high school graduates enrolling in community college would likely enroll at a CUNY 2-year, rather than leaving home to enroll at a SUNY 2-year (see next footnote). Thus, I can reasonably use this enrollment measure as a measure of enrollment in a in-state public 4-year institution.

[18] CUNY 2-year institutions include all public 2-year institutions located in New York City. 79% of community college students attend college within 20 miles from home (PowerStats 2025). Given the availability of several community colleges in the city, and my focus on recent high school graduates, I would expect the share of community college enrollees staying in the city to be even higher in my sample. Thus, I can reasonably use enrollment at a 2-year CUNY Institution as a measure of enrollment at any 2-year public in-state institution in my setting.

In order to alleviate concerns about this differential attrition biasing the results, I test for balance on observable baseline characteristics, by running the first stage in Equation 9 with each characteristic as the outcome. I then run an F-test of joint significance to test whether theme assignments jointly affect the baseline characteristic, indicating that there may be differential selection on the characteristic into treatment groups. In Table A6, I list the baseline characteristics as well as the p-value from the F-test. The only null hypothesis I fail to reject at the 10% level is that the theme assignment coefficients do not jointly predict whether students are female. I plot the full results from the balance check on female in Figure A6. In the future, I will run a robust specification of all theme enrollment results that controls for whether the applicant is female.

One caveat is that this framework assumes constant effects of each theme across students. In the future, rather than imposing this strong assumption, I will impose some weaker assumptions on individual preferences in order to identify the local average treatment effect of each theme on students who enroll in that theme instead of the theme of their counterfactual assignment (Kirkeboen et al. 2016).

11 Conclusion

In this paper, I investigate the implications of curricular themes for segregation and student outcomes in New York City high schools. I begin by presenting novel descriptive evidence on high school application and enrollment behavior with respect to theme. I then estimate a structural model of strategic application choice, which I use to identify preferences for each curricular theme, relative to the general high school theme. In order to better understand the impact of curricular themes on segregation and student welfare, I use my model estimates to simulate the counterfactual assignment that would occur without curricular differentiation. I find that though it may slightly increase racial segregation, curricular differentiation is overall not a major contributor to cross-high-school segregation in New York City. I also find that even if students on average prefer general programs, a substantial minority of students, including half of all black applicants in my setting, prefer specialized themed programs, and would lose out in a school system without curricular differentiation.

Finally, I estimate the effect of enrollment at each theme on high school outcomes and postsecondary enrollment. I find evidence that theme enrollment matters for high school outcomes, and potentially for postsecondary choice. There are no clear takeaways in terms of certain themes being worse or better for all student outcomes. I do not find evidence that students derive any additional benefit from enrolling at their favorite theme, indicating that curricular differentiation does not lead to efficiency gains in this setting.

Offering curricular heterogeneity and labeling school programs by curricular theme is a policy choice with important tradeoffs to consider. Previous work has documented the barriers faced by disadvantaged applicants in the application process (Sattin-Bajaj, Jennings, Corcoran, and Baker-Smith 2018). Given the complexity of the application process, and the inequities embedded in navigating such a complex process, the question of whether the benefit of an additional dimension of school differentiation outweighs the cost is an important one. My work suggests that curricular differentiation can improve applicant satisfaction with the match, but the allocation of general versus specialized theme capacity is important. I find that a substantial minority of students, including half of all black students would like their assigned program less in a world without curricular differentiation. However, the fact that the majority of students would be happier in this world suggests that the optimal distribution of enrollment seats by theme would include more general seats and fewer specialized theme seats. I also find that the impact of curricular differentiation on segregation is very small, allaying concerns about segregation as a potential cost of curricular differentiation. It is unclear whether curricular differentiation benefits student outcomes in aggregate, as sorting into themes on preference does not improve outcomes. Future work analyzing credit attainment by subject area and school finance data to learn more about the implementation of themes will provide additional insight into the costs and benefits of curricular differentiation.

As long as New York City and other urban school districts in the United States provide families with a large degree of choice, the extent to which the choices differ along dimensions like curricular theme is important. An understanding of student preferences over themes and their implications for student sorting and outcomes will help districts implement curricular differentiation in alignment with their objectives.

Tables

Table 1: Number of Programs Offered for the 2011-12 to 2017-18 School Years by Theme

Theme	**N**
Arts and Design	168
Business, Hospitality, and Services	65
Computing and Engineering	129
Humanities and Interdisciplinary	251
Media	40
Military and Law Enforcement	15
Multicultural	33
Public Service, Law, and Social Justice	74
Science	160
All	935

Table 2: New York City High School Applicant and Enrollee Descriptives

Group	City Share HS Applicants	City Share HS Enrollees	Group rate of high school enrollment at... Public NYC	Exam / Audition	Opt Out
Asian	0.19	0.20	0.96	0.23	0.03
Black	0.26	0.26	0.91	0.01	0.09
Hispanic	0.39	0.39	0.91	0.01	0.09
White	0.16	0.15	0.85	0.12	0.12
Not Poor	0.29	0.27	0.87	0.13	0.11
Poor	0.71	0.73	0.92	0.05	0.07
Low Ach.	0.25	0.25	0.91	0.00	0.08
Middle Ach.	0.36	0.36	0.90	0.00	0.09
High Ach.	0.39	0.39	0.91	0.19	0.07
Brooklyn	0.30	0.31	0.93	0.08	0.06
Manhattan	0.10	0.10	0.90	0.11	0.09
Queens	0.31	0.31	0.92	0.07	0.07
Staten Island	0.07	0.06	0.88	0.06	0.10
Bronx	0.22	0.22	0.87	0.02	0.12
N	366,082	332,040			

Notes: Contains all applicants in the sample. Public NYC refers to enrollment at a non-charter public high school (including Exam / Audition). Opt out refers to applicants who do not enroll at any non-charter NYC public high school. Enrollment is measured only in the year following application.

Table 3: School-Level Demographic Characteristics of New York City High School Programs, by Theme

Theme	Total Enrollment	Prop. Poor	Prop. ELL	Prop. Low Baseline Scores	Prop. High Baseline Scores
Arts and Design	1171	0.74	0.09	0.40	0.24
Business, Hospitality, and Services	1345	0.80	0.14	0.46	0.16
Computing and Engineering	1011	0.79	0.11	0.43	0.21
Humanities and Interdisciplinary	1003	0.75	0.12	0.39	0.25
Media	1363	0.73	0.12	0.39	0.25
Military and Law Enforcement	1627	0.74	0.08	0.46	0.19
Multicultural	592	0.86	0.52	0.62	0.11
Public Service, Law, and Social Justice	1295	0.79	0.10	0.41	0.22
Science	1332	0.77	0.11	0.36	0.27
All	1146	0.77	0.13	0.41	0.23

Notes: Program descriptives for all 935 programs offered from 2011-12 through 2017-18. School-level data from the first year a program appears is used.

Table 4: School-Level Graduation Outcomes of New York City High School Programs, by Theme

Theme	Prop. 6-year HS Grad	Prop. CTE Endorsement	Prop. 3+/4+ on AP/IB	Prop. Any College	Prop. In-State 4-year Public
Arts and Design	0.78	0.06	0.10	0.61	0.10
Business, Hospitality, and Services	0.72	0.07	0.07	0.56	0.07
Computing and Engineering	0.73	0.18	0.08	0.57	0.07
Humanities and Interdisciplinary	0.78	0.00	0.14	0.66	0.11
Media	0.80	0.06	0.11	0.63	0.08
Military and Law Enforcement	0.74	0.02	0.08	0.55	0.08
Multicultural	0.76	0.00	0.15	0.60	0.07
Public Service, Law, and Social Justice	0.77	0.00	0.10	0.65	0.10
Science	0.79	0.02	0.13	0.65	0.09
All	0.77	0.05	0.11	0.62	0.09

Notes: Program descriptives for all 935 programs offered from 2011-12 through 2017-18. School-level data from the first year a program appears is used. For graduation and postsecondary outcomes, the denominator is equal to the cohort of students who entered high school 6 years earlier.

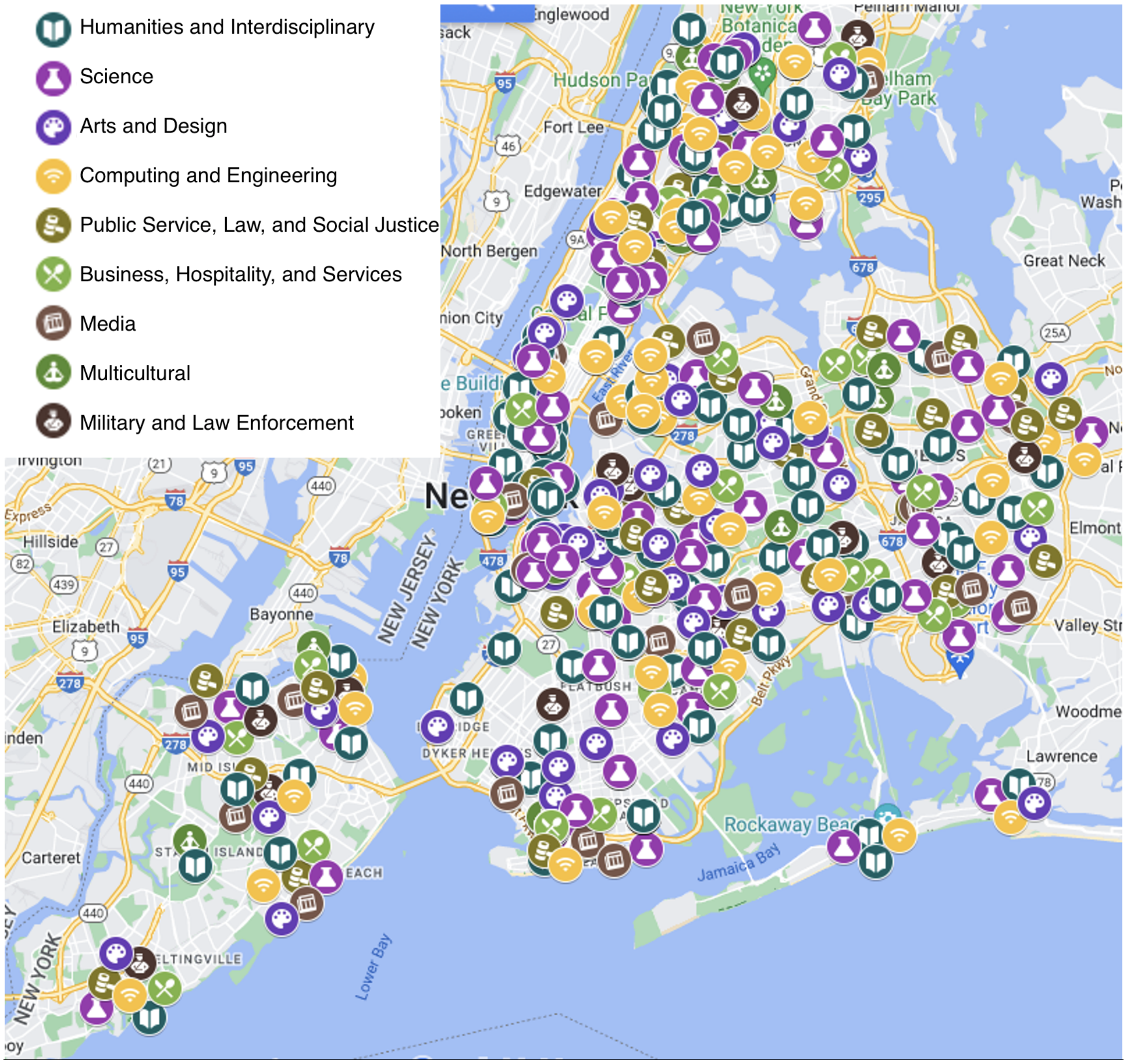
Table 5: Top Three Favorite Themes

Cell	1st favorite theme	2nd favorite theme	3rd favorite theme
Asian, non-low-income, high achievement	Computing and Engineering	Humanities and Interdisciplinary	Science
Asian, non-low-income, non-high achievement	Multicultural	Humanities and Interdisciplinary	Science
Asian, low-income, high achievement	Science	Computing and Engineering	Humanities and Interdisciplinary
Asian, low-income, non-high achievement	Multicultural	Science	Computing and Engineering
Black, non-low-income, high achievement	Science	Humanities and Interdisciplinary	Public Service, Law, and Social Justice
Black, non-low-income, non-high achievement	Science	Humanities and Interdisciplinary	Public Service, Law, and Social Justice
Black, low-income, high achievement	Science	Public Service, Law, and Social Justice	Humanities and Interdisciplinary
Black, low-income, non-high achievement	Science	Public Service, Law, and Social Justice	Humanities and Interdisciplinary
Hispanic, non-low-income, high achievement	Science	Humanities and Interdisciplinary	Computing and Engineering
Hispanic, non-low-income, non-high achievement	Humanities and Interdisciplinary	Public Service, Law, and Social Justice	Multicultural
Hispanic, low-income, high achievement	Science	Humanities and Interdisciplinary	Computing and Engineering
Hispanic, low-income, non-high achievement	Humanities and Interdisciplinary	Science	Public Service, Law, and Social Justice
White, non-low-income, high achievement	Humanities and Interdisciplinary	Science	Computing and Engineering
White, non-low-income, non-high achievement	Humanities and Interdisciplinary	Media	Business, Hospitality, and Services
White, low-income, high achievement	Science	Humanities and Interdisciplinary	Computing and Engineering
White, low-income, non-high achievement	Humanities and Interdisciplinary	Multicultural	Computing and Engineering

Notes: For each demographic cell, the top three preferred themes based on theme coefficient estimates.

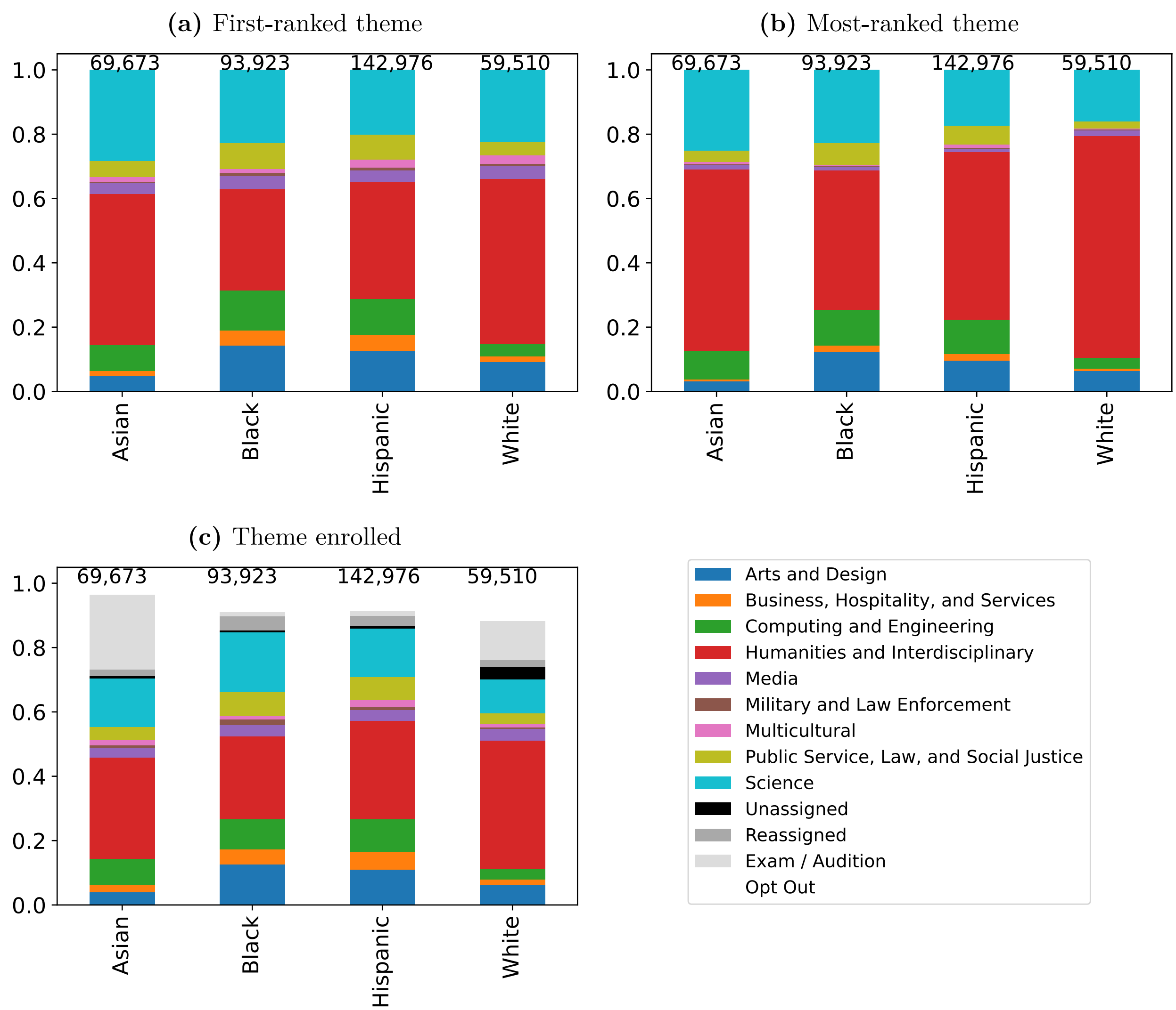
Figures

Figure 1: Distribution of Themed Programs Across New York City



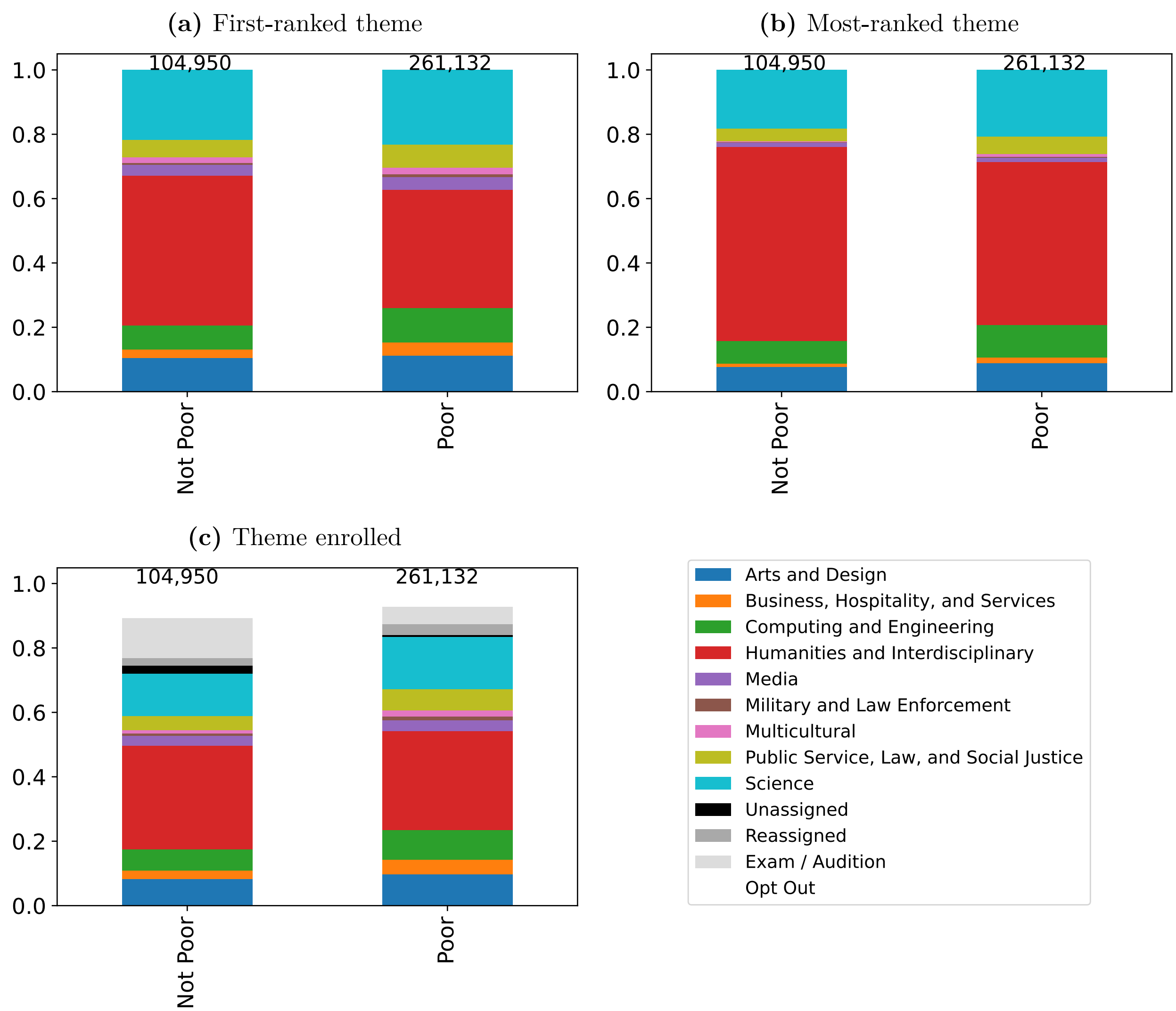
Notes: Locations of each program program offering from 2010-2019, plotted in Google Maps. Some programs are placed at a slight offset from their exact coordinates, so that multiple programs in the same location are visible.

Figure 2: Application and Enrollment Behavior with Respect to Themes, by Race



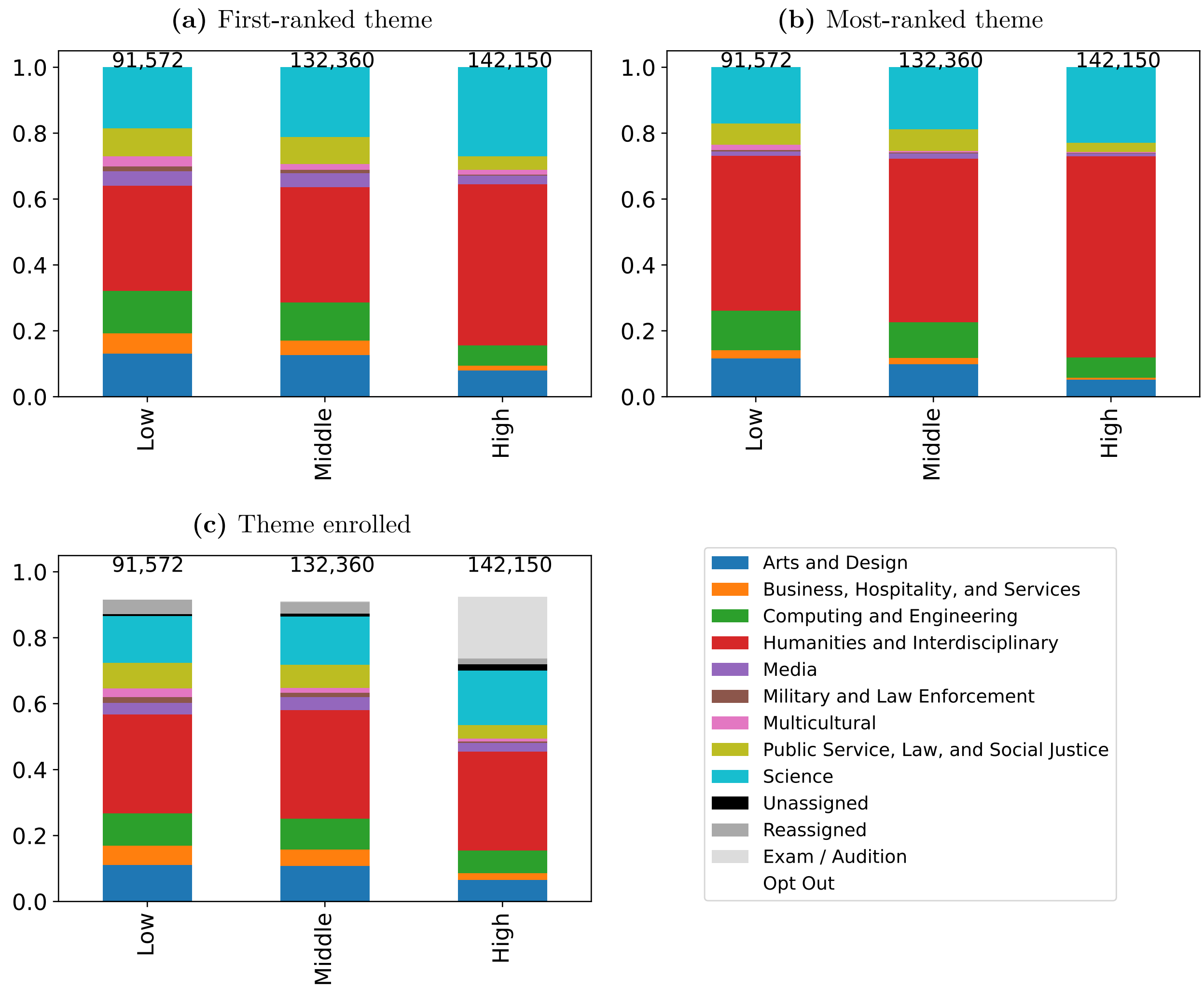
Notes: For each applicant in the sample from 2011-12 to 2017-18, I observe the theme they rank first, the theme they rank more than others (with ties broken by whichever theme was ranked earliest), and the theme they enrolled. I then plot the distribution of first ranked theme, most ranked theme, and theme enrolled, by race. All figures represent the same number of students; the empty space at the top of the bars in panel (c) represent the students who received a main round assignment but do not enroll at a New York City public high school. "Unassigned" refers to students who did not receive a main round assignment and do not enroll at a New York City public high school. "Reassigned" refers to students who enroll at a New York City public school that was not their main round assignment, and is not an Exam / Audition school.

Figure 3: Application and Enrollment Behavior with Respect to Themes, by Income



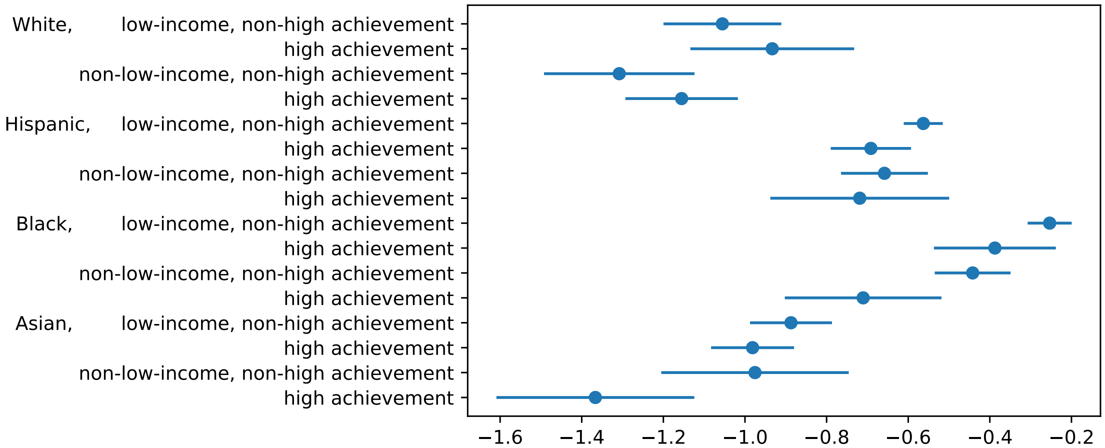
Notes: For each applicant in the sample from 2011-12 to 2017-18, I observe the theme they rank first, the theme they rank more than others (with ties broken by whichever theme was ranked earliest), and the theme they enrolled. I then plot the distribution of first ranked theme, most ranked theme, and theme enrolled, by income (measured by free- or reduced- price lunch eligibility). All figures represent the same number of students; the empty space at the top of the bars in panel (c) represent the students who received a main round assignment but do not enroll at a New York City public high school. "Unassigned" refers to students who did not receive a main round assignment and do not enroll at a New York City public high school. "Reassigned" refers to students who enroll at a New York City public school that was not their main round assignment, and is not an Exam / Audition school.

Figure 4: Application and Enrollment Behavior with Respect to Themes, by Achievement



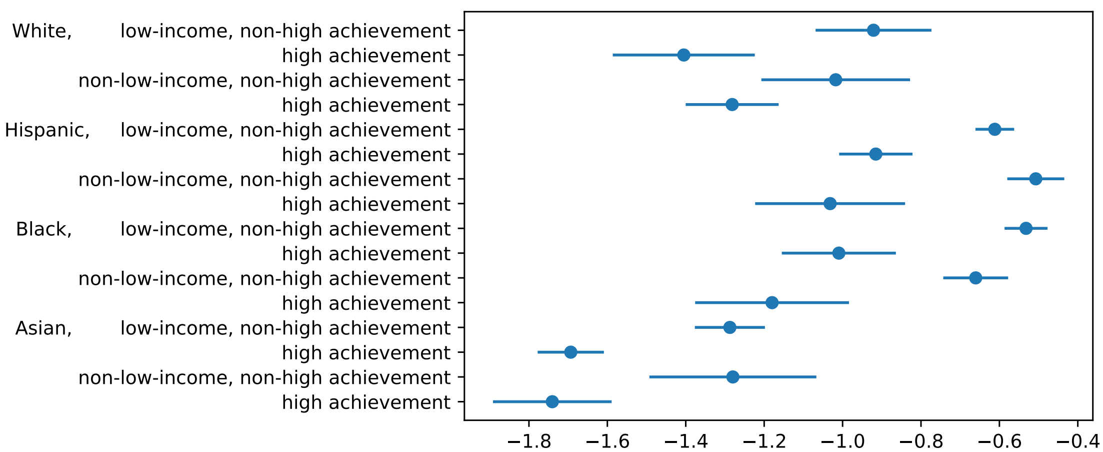
Notes: For each applicant in the sample from 2011-12 to 2017-18, I observe the theme they rank first, the theme they rank more than others (with ties broken by whichever theme was ranked earliest), and the theme they enrolled. I then plot the distribution of first ranked theme, most ranked theme, and theme enrolled, by baseline achievement. Baseline achievement is measured by percentile of 7th grade ELA and math test score, equally weighted, and split into the lowest third, middle third, and highest third. All figures represent the same number of students; the empty space at the top of the bars in panel (c) represent the students who received a main round assignment but do not enroll at a New York City public high school. "Unassigned" refers to students who did not receive a main round assignment and do not enroll at a New York City public high school. "Reassigned" refers to students who enroll at a New York City public school that was not their main round assignment, and is not an Exam / Audition school.

Figure 5: Preference for Themed Programs, Relative to Humanities and Interdisciplinary ϕ_{cell}



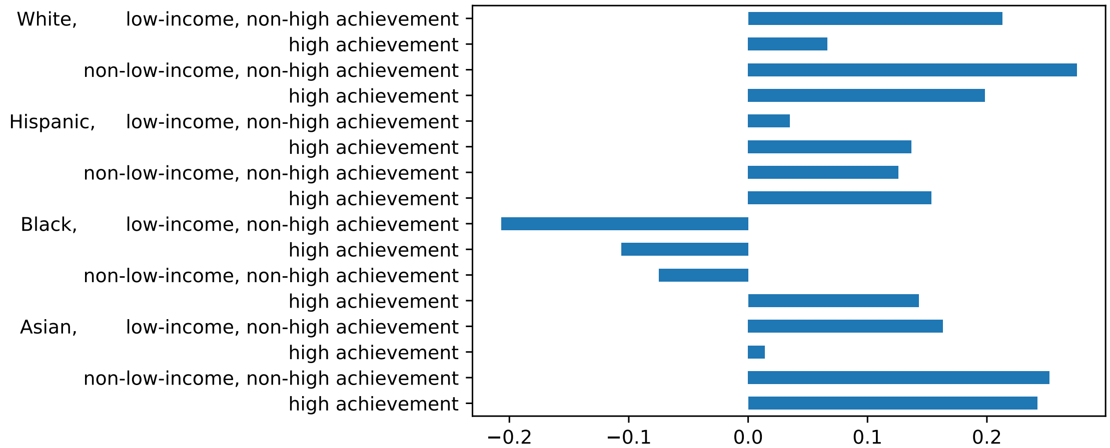
Notes: This figure shows 95% confidence intervals for estimated theme preference coefficients, ϕ_{cell}. The theme coefficient can be interpreted as the demographic cell's average preference for other themed programs, relative to the Humanities and Interdisciplinary theme.

Figure 6: Preference for Themed Programs, Relative to Humanities and Interdisciplinary and Science ϕ_{cell}



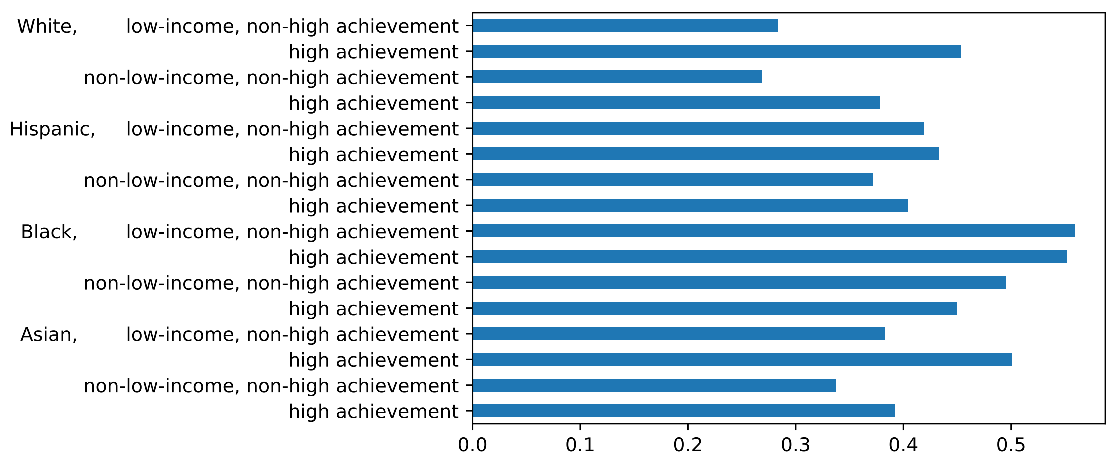
Notes: This figure shows 95% confidence intervals for estimated theme preference coefficients, ϕ_{cell}. The theme coefficient can be interpreted as the demographic cell's average preference for other themed programs, relative to Humanities and Interdisciplinary or Science themes.

Figure 7: Mean Change in Assigned Program Utility from Baseline Simulation to Counterfactual Simulation



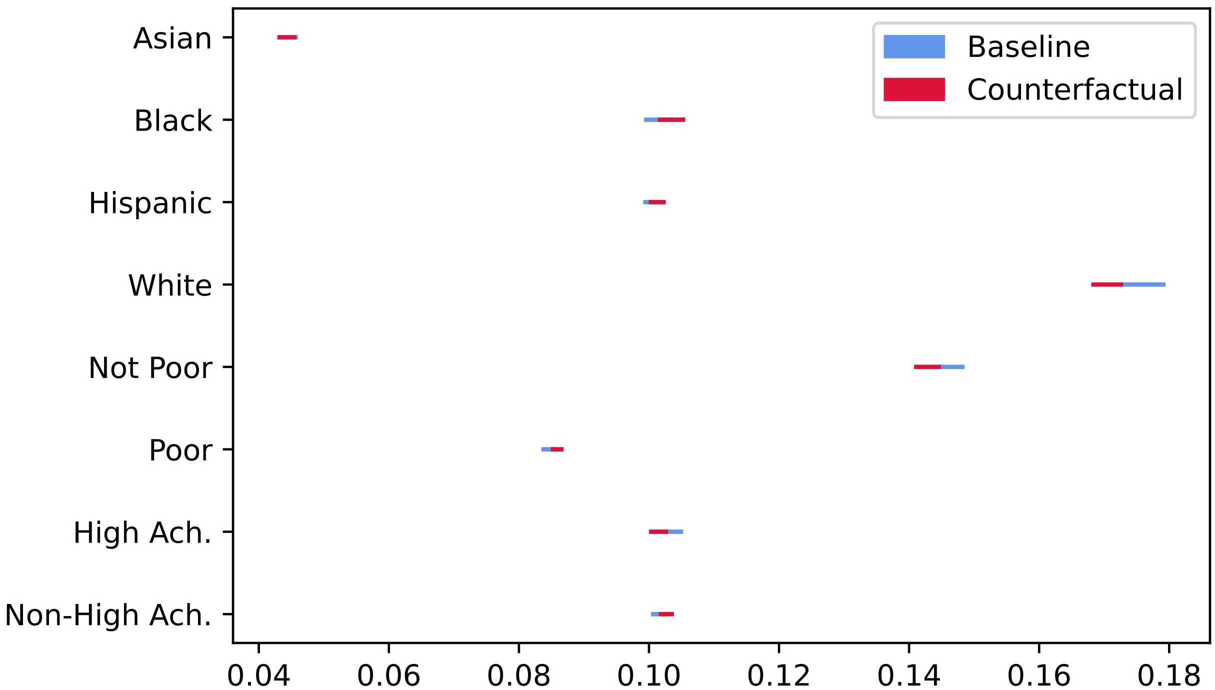
Notes: For each applicant, I subtract the utility of their assigned program in the simulated baseline from the utility of their assigned program in the simulated counterfactual. I plot the mean for each demographic group. These results are from only one simulation iteration, and will be updated after I run more iterations.

Figure 8: Proportion of Applicants Worse Off in the Counterfactual Simulation than in the Baseline Simulation



Notes: For each applicant, I subtract the utility of their assigned program in the simulated baseline from the utility of their assigned program in the simulated counterfactual. I plot the proportion for whom the change is negative for each demographic group. These results are from only one simulation iteration, and will be updated after I run more iterations.

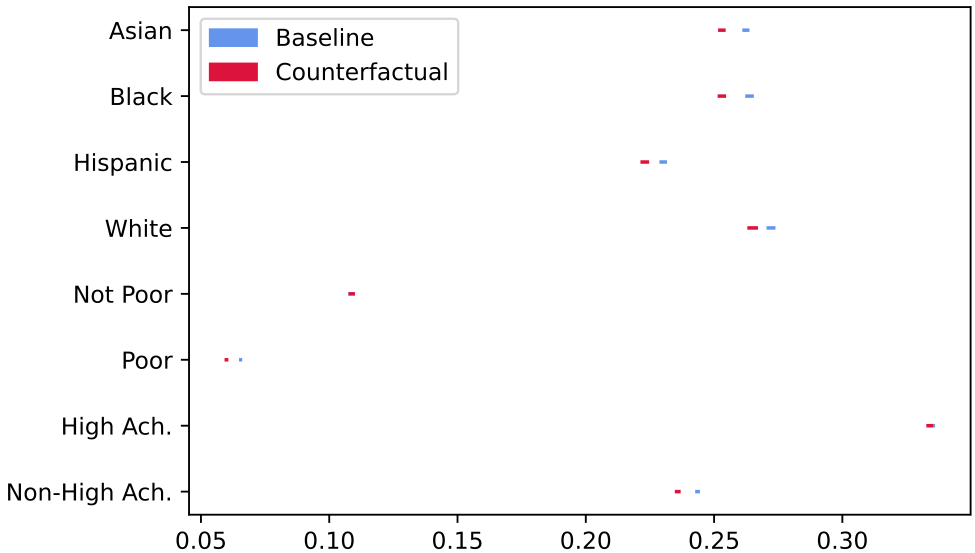
Figure 9: District Exit in All-Humanities and Interdisciplinary Counterfactual vs. Baseline



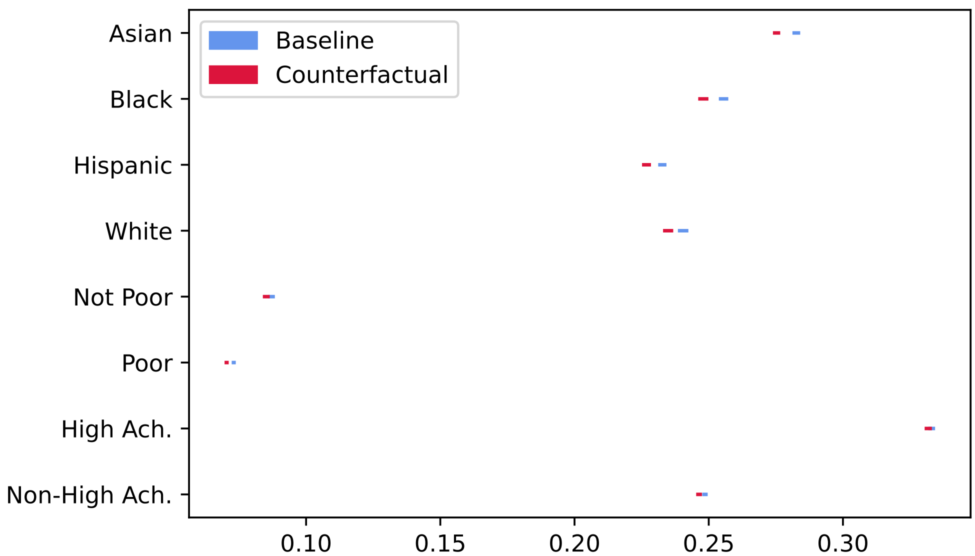
Notes: District exit refers to enrollment at a school at a school outside of the NYC centralized high school assignment system, and outside of the Exam / Audition category, at which I observe enrollment. The 95% confidence intervals for each group's rate of district exit at baseline is plotted in blue and in the counterfactual is plotted in red. These results are based on 100 iterations each of baseline and counterfactual simulation.

Figure 10: Cross-Program Segregation in All-Humanities and Interdisciplinary Counterfactual vs. Baseline

(a) Assigned Program



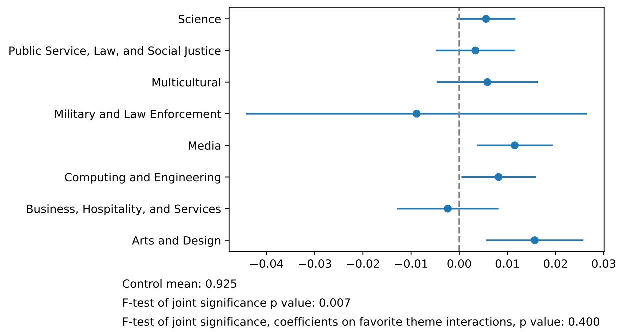
(b) Enrolled Program



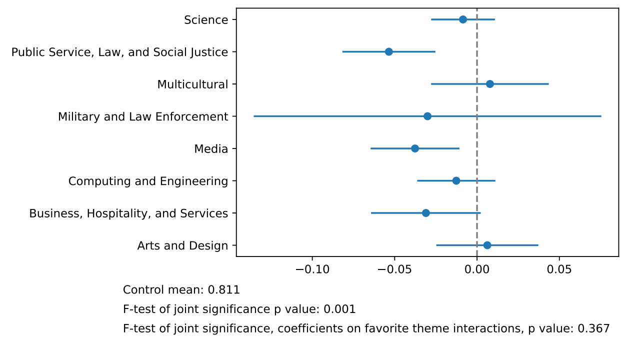
Notes: Segregation indices are computed according to 1, with same-group exposure computed within-cohort, and the mean taken over students in all years of the sample. The 95% confidence intervals for each group's excess isolation in the baseline is plotted in blue and in the counterfactual is plotted in red. These results are based on 100 iterations each of baseline and counterfactual simulation. Assigned program refers to a student's main round assignment, and enrolled program refers to the program where they enroll.

Figure 11: Theme Enrollment Effects

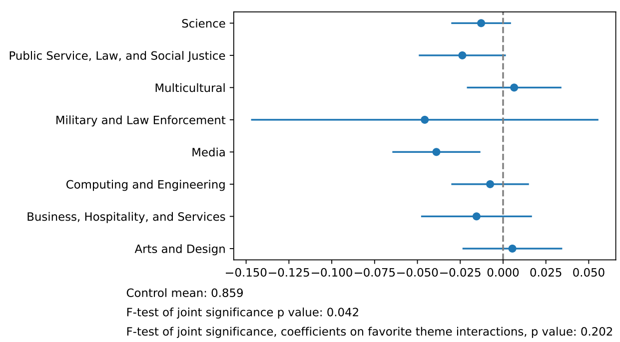
(a) Attendance rate in first year of high school



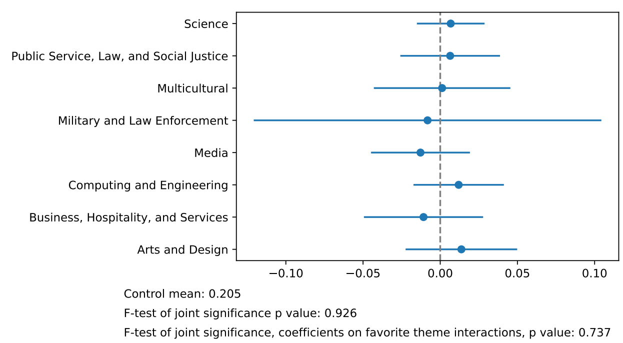
(b) Take the SAT



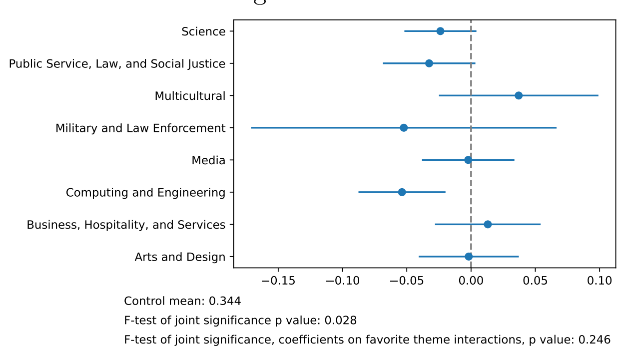
(c) Graduate in 4 years



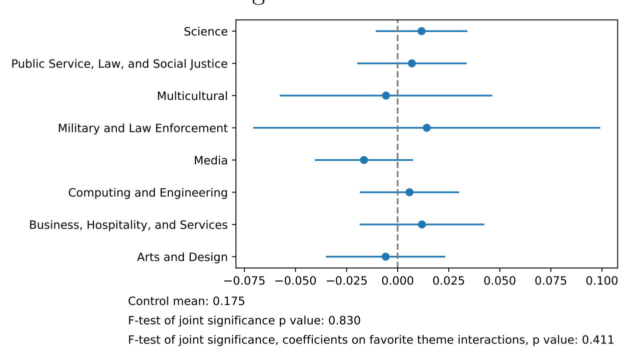
(d) Enroll at in-state public 2-year institution by the fall after on-time graduation



(e) Enroll at in-state public 4-year institution by the fall after on-time graduation



(f) Enroll at private or out-of-state institution by the fall after on-time graduation



Notes: Theme enrollment effects are estimated according to the specification in Equation 9, with robust standard errors. I plot the 95% confidence interval for each effect estimate. Plots include the control mean, the mean outcome among those enrolled at Humanities and Interdisciplinary or Exam / Audition programs, and the p-value from an F-test of joint significance of all plotted coefficients. They also include the p-value from the F-test of joint significance of all coefficients on preference interaction effects, from the interacted specification. Following Calonico, Cattaneo, and Titiunik 2014, I compute MSE-optimal bandwidths for a triangular kernel for 4-year high school graduation. The results currently displayed use the same bandwidth for all outcomes. "In-state public 2-year institution" refers any CUNY 2-year institution and "In-state public 4-year institution" refers to any SUNY or CUNY 4-year institution.

References

Abdulkadiroglu, Atila, Nikhil Agarwal, and Parag Pathak (2017). "The Welfare Effects of Coordinated Assignment: Evidence from the New York City High School Match?" In: *American Economic Review* 107.12, pp. 3635–3689.

Abdulkadiroglu, Atila, Joshua Angrist, et al. (2017). "Research Design Meets Market Design: Using Centralized Assignment for Impact Evaluation". In: *Econometrica* 85.5, pp. 1373–1432.

– (2022). "Breaking Ties: Regression Discontinuity Design Meets Market Design". In: *Econometrica* 90.1, pp. 117–151.

Abdulkadiroglu, Atila, Parag Pathak, et al. (2020). "Do Parents Value School Effectiveness?" In: *American Economic Review* 110.5, pp. 1502–1539.

Agarwal, Nikhil and Paulo Somaini (2018). "Demand Analysis Using Strategic Reports: An Application to a School Choice Mechanism". In: *Econometrica* 86.2, pp. 391–444.

Bifulco, Robert, Casey Cobb, and Courtney Bell (2009). "Can Interdistrict Choice Boost Student Achievement? The Case of Connecticut's Interdistrict Magnet School Program". In: *Educational Evaluation and Policy Analysis* 31.4, pp. 323–345.

Black, Sandra (1999). "Do Better Schools Matter? Parental Valuation of Elementary Education". In: *The Quarterly Journal of Economics* 114.2, pp. 577–599.

Bloom, Howard and Rebecca Unterman (2014). "Can Small High Schools of Choice Improve Educational Prospects for Disadvantaged Students?" In: *Journal of Policy Analysis and Management* 33.2, pp. 290–319.

Brunner, Eric, Shaun Dougherty, and Stephen Ross (2021). "The Effects of Career and Technical Education: Evidence from the Connecticut Technical High School System". In: *NBER Working Paper 28790*.

Buder, Leonard (1975). "'Magnet' High Schools in City Are Pulling". In: *The New York Times*.

Burgess, Simon et al. (2014). "What Parents Want: School Preferences and School Choice". In: *The Economic Journal* 125.587, pp. 1262–1289.

Caetano, Gregorio and Hugh Macartney (2021). "What determines school segregation? The crucial role of neighborhood factors". In: *Journal of Public Economics* 193, pp. 2–19.

Calonico, Sebastian, Matias Cattaneo, and Rocio Titiunik (2014). "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs". In: *Econometrica* 82.6, pp. 2295–2326.

Corcoran, Sean et al. (2018). "Leveling the Playing Field for High School Choice: Results from a Field Experiment of Informational Interventions". In: *NBER Working Paper 24471*.

Crespin, Rene (2023). "The Value of School Social Climate Information: Evidence from Chicago Housing Transactions". In: *Working Paper*.

Dobbie, Will and Roland Fryer (2013). "Getting Beneath the Veil of Effective Schools: Evidence from New York City". In: *American Economic Journal: Applied Economics* 5.4, pp. 28–60.

Dougherty, Shaun (2018). "The Effect of Career and Technical Education on Human Capital Accumulation: Causal Evidence from Massachusetts". In: *Education Finance and Policy* 13.2, pp. 119–148.

Hahm, Dongwoo and Minseon Park (2022). "A Dynamic Framework of School Choice Effects of Middle Schools on High School Choice". In: *Working Paper*.

Hailey, Chantal (2022). "Racial Preferences for Schools: Evidence from an Experiment with White, Black, Latinx, and Asian Parents and Students". In: *Sociology of Education* 95.2, pp. 110–132.

Hastings, Justine, Thomas Kane, and Douglas Staiger (2008). "Heterogeneous Preferences and the Efficacy of Public School Choice". In: *Working Paper*.

Hemphill, Clara and Kim Nauer (2009). *The New Marketplace: How Small-School Reforms and School Choice Have Reshaped New York City's High Schools*. The New School Center for New York City Affairs.

Idoux, Clemence (2021). "Integrating New York City Schools: The Role of Admission Criteria and Family Preferences". In: *Working Paper*.

Jacob, Brian and Michael Ricks (2023). "Why Choose Career Technical Education? Disentangling Student Preferences from Program Availability". In: *Working Paper*.

Kirkeboen, Lars J., Edwin Leuven, and Magne Mogstad (2016). "Field of Study, Earnings, and Self-Selection". In: *The Quarterly Journal of Economics* 131.3, pp. 1057–1112.

Laverde, Mariana (2022). "Distance to Schools and Equal Access in School Choice Systems". In: *Working Paper*.

Massey, Douglas and Nancy Denton (1988). "The Dimensions of Residential Segregation". In: *Social Forces* 67.2, pp. 281–315.

McCulloch, Robert, Peter Rossi, and Greg Allenby (1996). "The Value of Purchase History Data in Target Marketing". In: *Marketing Science* 15.4, pp. 321–340.

Monarrez, Tomas (2023). "School Attendance Boundaries and the Segregation of Public Schools in the United States". In: *American Economic Journal: Economic Policy* 15.3, pp. 210–237.

Monarrez, Tomas, Brian Kisada, and Matthew Chingos (2022). "The Effect of Charter Schools on School Segregation". In: *American Economic Journal: Economic Policy* 14.1, pp. 301–340.

Morgan, Malcolm et al. (2023). *OpenTripPlanner*. Version 1.5; 2.3. URL: https://www.opentripplanner.org.

New York City Department of Education (2022a). *Demographic Snapshot (2006-12, 2011-16, 2013-16, 2018-19, 2019-20)*. Last accessed 2023-03-01.

– (2022b). *DOE High School Directories, 2010-11 through 2019-20*. Last accessed 2023-02-01.

– (2022c). *Graduation results for Cohorts 2001 to 2011, 2012 to 2019*. Last accessed 2023-03-01.

– (2022d). *School Quality Reports, 2010-11 through 2019-20*. Last accessed 2023-03-01.

New York State Education Department (2024). *NY State Public School Enrollment (2022 - 23)*. Last accessed 2024-06-09. URL: https://data.nysed.gov/enrollment.php?state.

NYC Department of Education (2023). *High School*. Last accessed 2024-06-09. URL: https://www.schools.nyc.gov/enrollment/enroll-grade-by-grade/high-school.

– (2024a). *DOE Data at a Glance*. Last accessed 2024-06-09. URL: https://www.schools.nyc.gov/about-us/reports/doe-data-at-a-glance.

NYC Department of Education (2024b). *National Assessment of Educational Progress (NAEP) Mathematics and Reading*. Last accessed 2024-06-09. URL: https://infohub.nyced.org/docs/default-source/default-document-library/2022-naep-nyc-results---webdeck---accessible.pdf.

Office of Elementary and Secondary Education (2024). *Magnet Schools Assistance Program*. Last accessed 2024-06-09. URL: https://oese.ed.gov/offices/office-of-discretionary-grants-support-services/school-choice-improvement-programs/magnet-school-assistance-program-msap/.

Oosterbeek, Hessel, Sandor Sovago, and Bas van der Klaauw (2021). "Preference heterogeneity and school segregation". In: *Journal of Public Economics* 197, pp. 1–26.

PowerStats (2025). *National Postsecondary Student Aid Study: 2016 Undergraduates. Distance from student's home (in miles) to NPSAS institution. Filtered by Highest level of offering at NPSAS institution (At least 2, but less than 4 academic years).* Last accessed 2025-10-17. URL: https://nces.ed.gov/datalab/powerstats/121-national-postsecondary-student-aid-study-2016-undergraduates/percentage-distribution.

Quint, Janet C. et al. (2010). *New York City's Changing High School Landscape: High Schools and Their Characteristics, 2002-2008*. MDRC.

Rossell, Christine (2003). "The Desegregation Efficiency of Magnet Schools". In: *Urban Affairs Review* 38.5, pp. 697–725.

Sattin-Bajaj, Carolyn et al. (2018). "Surviving at the Street Level: How Counselors' Implementation of School Choice Policy Shapes Students' High School Destinations". In: *Sociology of Education* 91.1, pp. 46–71.

United States Census Bureau (2023). *Centers of Population by Census Tract, New York (2010,2020)*. Last accessed 2023-03-01.

Walters, Christopher (2018). "The Demand for Effective Charter Schools". In: *Journal of Political Economy* 126.6, pp. 2179–2223.

Wiswall, Matthew et al. (2014). "Does attending a STEM high school improve student performance? Evidence from New York City". In: *Economics of Education Review* 40, pp. 93–105.

APPENDIX

A Definition of Program Themes

After proposing this study to the New York City Department of Education, they suggested I propose and refine a categorization of high school programs to be used. I was guided by their advice to base the theme categories not solely on academic interest area, as assigned in the program directories, but also on the program name, which contains additional information on theme.

I began with the New York City Department of Education high school program directories for the years 2014-2020, from the NYC Open Data website. I divided these programs by curricular theme into nine categories: Arts and Design; Business, Hospitality, and Services; Computing and Engineering; Humanities and Interdisciplinary; Media; Military and Law Enforcement; Multicultural; Public Service, Law, and Social Justice; and Science.

My categorization is based on the interest area categorization in the directory, as well as the words contained in the program name.

A.1 Methodology

I began thinking about the program categorization with the DOE interest areas in mind. By looking at the programs within each interest area, I decided which interest areas my categorization should keep intact, and which interest areas my categorization should split. I kept the following interest areas intact, ultimately assigning all their programs to the same category:

Interest area in directory	Category
Culinary Arts	Business, Hospitality, and Services
Cosmetology	
Hospitality, Travel, and Tourism	
Computer Science & Technology	Computing and Engineering
Computer Science, Math & Technology	
Zoned	Humanities, Interdisciplinary, and General
Project-Based Learning	
JROTC	Military and Law Enforcement
Communications	Media
Film/Video	
Teaching	Public Service, Law, and Social Justice
Animal Science	Science
Environmental Science	Science
Health Professions	Science
Architecture	Arts and Design
Performing Arts	
Performing Arts/Visual Art & Design	
Visual Art & Design, and Performing Arts	
Visual Art & Design	

I decided to split the interest areas listed below, based on divisions between their programs that I observed. For each of these interest areas, I explain below why I thought it made sense to split up the programs into different categories, and the categorization rules:

- Humanities and Interdisciplinary
  - Within this interest area, I saw some programs that would seem to fit better under other already-defined categories, or under their own new category.
  - Program names including the words "International" (not "International Baccalaurate" or "International Marketing"), "Multicultural", "Global", "Diversity", "Diplomacy", or "World Cultures" were placed in Multicultural.
  - Program names including the words "Civil Rights", "Leadership", "Social", "Public Service", "Community Service", "Human Rights", "Civic", or "Peace" were placed in Public Service, Law, and Social Justice.
  - Program names including the words "Enforcement", "Safety", "Crim", or "Forensics" were placed in Military and Law Enforcement.
  - Program names including the words "Media" or "Communication" were placed in Media.
  - Program names including the words "Marketing" or "Sports Management" were placed in Business, Hospitality, and Services.

  - Program names including the word "Environmental" were placed in Science.
  - The remaining programs ended up in Humanities, Interdisciplinary, and General.

- Science and Math
  - Within this area, there were some programs that were related to computing or IT.
  - Program names including "Computer" or "Information Technology" were placed in Computing and Engineering
  - The remaining programs ended up in Science.

- Business
  - Within this area, there were some programs that were related to computing or IT.
  - Program names including "Computer" or "Information Technology" were placed in Computing and Engineering
  - The remaining programs ended up in Business, Hospitality, and Services.

- Law & Government
  - Within this area, some programs seemed more related to public safety, while others to social justice, activism, law, or government.
  - Program names including the words "Enforcement", "Safety", "Crim", or "Forensics" were placed in Military and Law Enforcement.
  - The remaining programs ended up in Public Service, Law, and Social Justice.

B Computing Public Transit Travel Times

I compute the travel distance from the population-weighted centroid of each NYC residential census tract to each NYC high school (United States Census Bureau 2023) [19].

I use OpenTripPlanner, an open-source project that enables analysis of transport networks (Morgan, Young, Lovelace, and Hama 2023). Given publicly available formatted source files representing New York and New Jersey street maps and New York City public transit (including subway, bus, PATH, ferry, and more), it sets up a server on my computer that can handle walk and public transit routing requests.

For each census tract centroid – high school pair, I request the latest walk and public transit route from the centroid coordinates that arrives at the high school coordinates by 8 AM on Thursday, March 23 2023. The duration of this route is my travel time measure.

[19] New York City does not offer school buses for high school students. High school students who live more than half a mile away from their school are eligible for a free MetroCard allowing three trips a day on school days (NYC Department of Education 2023)

First, I use OTP 1.5 to get the times in batches for each school (batch travel times are not implemented for 2.3). Then, I fill in missing travel times with one-to-one calls to the OTP 2.3 server. OTP 2.3 uses an improved routing algorithm, but both 1.5 and 2.3 find the best route.

C Computing Assignment Probabililties

I follow the formulas in Idoux (2021) for computing assignment probabilities from admit probabilities in a way that captures interdependencies from the shared tiebreaker. I assume the applicant treats admissions events as independent across score programs, conditional on their information set. While this assumption may deviate slightly from belief consistency, screened programs place different weights on admit criteria, and can be subjective, limiting the extent to which these admit outcomes are actually interdependent.

Transform all applicant tiebreakers to be within $[0,1]$. The winners of the lottery are those below the cutoff value. The probability that applicant i is assigned to score program j if ranked in slot k after R_{k-1} equals:

$$p_{ijk}(R_{k-1}) = q_{ij} \times \underbrace{(1 - \max_{sL^l:\{r_{is}<k\}} q_{is})}_{\substack{\mathbb{P}[\text{rejected from higher-ranked} \\ \text{lottery programs}]}} \underbrace{\prod_{sL^s:r_{is}<k} (1 - q_{is})}_{\substack{\mathbb{P}[\text{rejected from higher-ranked} \\ \text{score programs}]}} \tag{11}$$

The probability that applicant i is assigned to lottery program j if ranked in slot k after R_{k-1} equals:

$$p_{ijk}(R_{k-1}) = \underbrace{\max\left[0, q_{ij} - \max_{sL^l:r_{is}<k} q_{is}\right]}_{\substack{\mathbb{P}[\text{rejected from higher-ranked} \\ \text{lottery programs and} \\ \text{accepted to } j]}} \underbrace{\prod_{sL^s:\{r_{is}<k\}} (1 - q_{is})}_{\substack{\mathbb{P}[\text{rejected from higher-ranked} \\ \text{score programs}]}} \tag{12}$$

D Bounds on Costs and Utilities Implied by Assumption 1 (Proposition 1, Idoux (2021))

I list the bounds on costs and utilities, derived in Idoux (2021) as implications of Assumption 1. I use these bounds for estimation.

1. For all applicants i, for any program j listed k^{th} in their list R_i, $p_{ijk}v_{ij} \geq c_i$. That is, applicant i's expected utility of ranking j in slot k is weakly higher than their marginal application cost.

2. For all applicants i who ranked $listlength$ programs, for any unlisted program j, $p_{ij,listlength}v_{ij} < c_i$. That is, applicant i's expected utility of adding j at the end of their list is less than their marginal application cost.

3. Each program j in R_i has indirect utility (v_{ij}) lower than all programs listed above it and higher than all those listed below it.

4. For all applicants i, for any program j listed in slot k, and any unlisted program j' such that $p_{ij'k}v_{ij} \geq c_i$, $v_{ij} \geq v_{ij'}$. That is, the program that applicant i chose for slot k must have indirect utility weakly higher than the indirect utilities of all other programs in their consideration set for slot k.

E Gibbs Sampler

The indirect utility for applicant i of assignment to program j is v_{ij}, where
$\boldsymbol{\gamma_{cell(i),ms(i),t(i)}} \sim MultivariateNormal(\mathbf{0}, \boldsymbol{\Sigma}_\gamma)$, and $\epsilon_{ij} \sim Normal(0, \sigma_\epsilon)$.

$$v_{ij} := \delta_{cell(i),j} + \theta_{boro(i),boro(j)} + \mathbf{X_{ij,t(i)-1}}\boldsymbol{\beta_{cell(i)}} - d_{ij} + \gamma_{cell(i),ms(i),t(i),theme(j)} + \epsilon_{ij} \quad (13)$$

and the per-program application cost is parameterized as c_i, where
$\zeta_i \sim TruncatedNormal(-c, \infty, 0, \sigma_\zeta)$

$$c_i = c + \zeta_i \quad (14)$$

My parameters of interest include program-by-cell fixed effects $\{\delta_{cell,j}\}$, residential borough-by-school borough fixed effects $\{\theta_{boro,boro}\}$, coefficients on time-varying lagged peer characteristics $\{\boldsymbol{\beta_{cell}}\}$, unobserved theme preference covariance matrix $\boldsymbol{\Sigma}_\gamma$, taste shock variance σ_ϵ, mean marginal cost c, and marginal cost variance σ_ζ. I estimate these parameters with data augmentation, drawing values of $\{v_{ij}\}$, $\{c_i\}$ and $\{\boldsymbol{\gamma_{cell,ms,t}}\}$ from their conditional posteriors at each step, because it is easier to sample my parameters of interest conditional on them. I normalize scale by setting the coefficient on travel time to -1, and I normalize location by setting the outside option indirect utility for each individual to ϵ_{i0}.

I initialize $\{\delta_{cell,j}\}$, $\{\theta_{boro,boro}\}$, and $\{\boldsymbol{\beta_{cell}}\}$ to 0, and $\boldsymbol{\Sigma}_\gamma$, σ_ϵ, and σ_ζ to 100. I initialize $\{c_i\}$, and $\{\gamma_{cell,ms,t,theme}\}$ to 0. I initialize indirect utilities $\{v_{ij}\}$ to values consistent with the bounds implied by the limited rationality assumption.

The parameter priors are $\delta_{cell,j} \sim N(\mu^0_{\delta_{cell,j}}, V^0_{\delta_{cell,j}})$, $\theta_{boro,boro} \sim N(\mu^0_{\theta_{boro,boro}}, V^0_{\theta_{boro,boro}})$, $\boldsymbol{\beta_{cell}} \sim N(\boldsymbol{\mu^0_{\beta_{cell}}}, \mathbf{V^0_{\beta_{cell}}})$, $c \sim TruncatedNormal(0, \infty, \mu^0_c, V^0_c)$, $\boldsymbol{\Sigma}_\gamma \sim InverseWishart(v^0_{\Sigma_\gamma}, \mathbf{V^0_{\Sigma_\gamma}})$, $\sigma_\epsilon \sim InverseWishart(v^0_{\sigma_\epsilon}, V^0_{\sigma_\epsilon})$, and $\sigma_\zeta \sim InverseWishart(v^0_{\sigma_\zeta}, V^0_{\sigma_\zeta})$. I choose fairly diffuse priors, to minimize their contribution to the results: $\mu^0_{\delta_{cell,j}} = 0$, $V^0_{\delta_{cell,j}} = 100$, $\mu^0_{\theta_{boro,boro}} = 0$, $V^0_{\theta_{boro,boro}} = 100$, $\boldsymbol{\mu^0_{\beta_{cell}}} = \left(\begin{smallmatrix}0\\0\end{smallmatrix}\right)$, $\mathbf{V^0_{\beta_{cell}}} = \left(\begin{smallmatrix}100 & 0\\0 & 100\end{smallmatrix}\right)$, $\mu^0_c = 0$, $V^0_c = 100$, $v^0_{\Sigma_\gamma} = 12$, $\mathbf{V^0_{\Sigma_\gamma}} = 12 \times \boldsymbol{I_9}$, $v^0_{\sigma_\epsilon} = 3$, $V^0_{\sigma_\epsilon} = 3$, $v^0_{\sigma_\zeta} = 3$, and $V^0_{\sigma_\zeta} = 3$.

On each iteration, I perform the following steps in order:

1. Sample $\{\delta_{cell,j}\}$ from $N(\mu^1_{\delta_{cell,j}}, V^1_{\delta_{cell,j}})$.
    - $R_{ij} = v_{ij} + d_{ij} - \theta_{boro(i),boro(j)} - \mathbf{X_{ij,t(i)-1}}\boldsymbol{\beta_{cell(i)}} - \gamma_{cell(i),ms(i),t(i),theme(j)}$

- $V^1_{\delta_{cell,j}} = \frac{\sum_{\text{i,j}} \mathbb{I}[cell(\text{i})=cell,\text{j}=j]}{\sigma_\epsilon} + \frac{1}{V^0_{\delta_{cell,j}}}$
- $\mu^1_{\delta_{cell,j}} = V^1_{\delta_{cell,j}} \times (\frac{\sum_{\text{i,j}} R_{ij}\mathbb{I}[cell(\text{i})=cell,\text{j}=j]}{\sigma_\epsilon} + \frac{\mu^0_{\delta_{cell,j}}}{V^0_{\delta_{cell,j}}})$

2. Sample $\{\boldsymbol{\beta_{cell}}\}$ from $N(\boldsymbol{\mu^1_{\beta_{cell}}}, \mathbf{V^1_{\beta_{cell}}})$.
   - $R_{ij} = v_{ij} + d_{ij} - \delta_{cell(i),j} - \theta_{boro(i),boro(j)} - \gamma_{cell(i),ms(i),t(i),theme(j)}$
   - For each cell, let $\mathbf{X(cell)}$ and $\mathbf{R(cell)}$ equal the stacked matrix of observations of $\mathbf{X_{ij,t(i)-1}}$ and R_{ij} for applicants in the cell, respectively.
   - $\mathbf{V^1_{\beta_{cell}}} = (\frac{\mathbf{(X(cell)'X(cell)}}{\sigma_\epsilon} + (\mathbf{V^0_{\beta_{cell}}})^{-1})^{-1}$
   - $\boldsymbol{\mu^1_{\beta_{cell}}} = \mathbf{V^1_{\beta_{cell(i)}}}(\frac{\mathbf{(X(cell)'R(cell)}}{\sigma_\epsilon} + (\mathbf{V^0_{\beta_{cell}}})^{-1}\boldsymbol{\mu^0_{\beta_{cell}}}$
3. Sample $\{\boldsymbol{\gamma_{cell,ms,t}}\}$ from $N(\boldsymbol{\mu^1_{\gamma_{cell,ms,t,theme}}}, \mathbf{V^1_{\gamma_{cell,ms,t}}})$.
   - $R_{ij} = v_{ij} + d_{ij} - \delta_{cell(i),j} - \theta_{boro(i),boro(j)} - \mathbf{X_{ij,t(i)-1}}\boldsymbol{\beta_{cell(i)}}$. Only the differences between preference for each theme are identified, so normalize R_{ij} so that mean residuals by theme add up to 0 within-cell-by-middle school cohort.
   - For each cell, middle school, and year combination, let $\boldsymbol{N}_{cell,ms,t}$ equal a vector where each element equals the number of observations within each theme. Let $\boldsymbol{R}_{cell,ms,t}$ equal a vector where each element equals the sum of residuals R_{ij} within each theme.
   - $\mathbf{V^1_{\gamma_{cell,ms,t}}} = (\frac{\mathbf{diag}(\boldsymbol{N}_{cell,ms,t})}{\sigma_\epsilon} + \boldsymbol{\Sigma}_\gamma{}^{-1})^{-1}$
   - $\mu^{\mathbf{1}}_{\gamma_{\mathbf{cell,ms,t}}} = \mathbf{V^1_{\gamma_{cell,ms,t}}} \times \frac{\boldsymbol{R}_{cell,ms,t}}{\sigma_\epsilon}$
4. Sample $\boldsymbol{\Sigma}_\gamma$ from $InverseWishart(\boldsymbol{N}_{cell,ms,t} + v^0_{\Sigma_\gamma}, \boldsymbol{\gamma'\gamma} + V_{\Sigma^0_\gamma})$, where $\boldsymbol{\gamma}$ is a stacked matrix of all $\boldsymbol{\gamma_{cell,ms,t}}$.
5. Sample $\{\theta_{boro,boro}\}$ from $N(\mu^1_{\theta_{boro,boro}}, V^1_{\theta_{boro,boro}})$.
   - $R_{ij} = v_{ij} + d_{ij} - \delta_{cell(i),j} - \mathbf{X_{j,t(i)-1}}\boldsymbol{\beta_{cell(i)}} - \gamma_{cell(i),ms(i),t(i),theme(j)}$. Only the differences between preferences for each high school borough are identified, so normalize R_{ij} so that mean residuals by high school borough add up to 0 within residential borough.
   - $V^1_{\theta_{rb,hb}} = \frac{\sum_{\text{i,j}} \mathbb{I}[\text{residential boro(i)}=rb\text{, high school boro(j)}=hb]}{\sigma_\epsilon} + \frac{1}{V^0_{\theta_{rb,hb}}}$
   - $\mu^1_{\theta_{rb,hb}} = V^1_{\theta_{rb,hb}} \times (\frac{\sum_{\text{i,j}} \mathbb{I}[\text{residential boro(i)}=rb\text{, high school boro(j)}=hb]R_{ij}}{\sigma_\epsilon} + \frac{\mu^0_{\theta_{rb,hb}}}{V^0_{\theta_{rb,hb}}})$
6. Sample σ_ϵ from $InverseWishart(N \times |CS(i)| + v^0_{\sigma_\epsilon}, \epsilon'\epsilon + V^0_{\sigma_\epsilon})$
   - N is the number of applicants, $|CS(i)| = 30$ is number of programs in each applicant's program choice set
   - $\epsilon_{ij} = v_{ij} + d_{ij} - \delta_{cell(i),j} - \theta_{boro(i),boro(j)} - \mathbf{X_{ij,t(i)-1}}\boldsymbol{\beta_{cell(i)}} - \gamma_{cell(i),ms(i),t(i),theme(j)}$
7. Sample $\{v_{ij}\}$ from $TN(lower_{ij}, upper_{ij}, mean_{v_{ij}}, \sigma_\epsilon)$, where $lower_{ij}$ and $upper_{ij}$ are based on the bounds in Appendix D.

- $mean_{v_{ij}} = \delta_{cell(i),j} + \theta_{boro(i),boro(j)} + \mathbf{X_{ij,t(i)-1}}\boldsymbol{\beta_{cell(i)}} - d_{ij} + \gamma_{cell(i),ms(i),t(i),theme(j)}$

8. Sample c from $TN(\mu_c^1, \sigma_c^1, 0, \infty)$.
   - $\sigma_c^1 = (N/\sigma_\zeta + 1/\sigma_c^0)^{-1}$
   - $\mu_c^1 = \sigma_c^1((\sum_i c_i)/\sigma_\zeta + \mu_c^0/\sigma_c^0)$
9. Sample σ_ζ from $IW(N + v^0_{\sigma_\zeta}, \sum_i (c_i^0 - c^1)^2 + V^0_{\sigma_\zeta})$
10. Sample $\{c_i\}$ from $TN(lower_{ij}, upper_{ij}, c, \sigma_\zeta)$, where $lower_{ij}$ and $upper_{ij}$ are based on the bounds in Appendix D.

After discarding the first 8000 iterations, I used the subsequent 1600 iterations for my estimates. I test for convergence by simulating 3 chains with different starting values. After 8000 iterations, 95 percent of parameters have a potential scale reduction factor of less than 1.1, indicating that the distribution of draws from the sampler has converged to the joint posterior distribution of all parameters.

F General Differences in Application and Enrollment, Baseline vs. Baseline Simulation vs. Counterfactual Simulation

For each applicant, I compute the difference in the simulated counterfactual program utility and the simulated baseline program utility, for each program in their choice set. Choice sets are fixed across simulations. Figure A3a shows the mean change in program choice set utility for each demographic cell. In the Humanities and Interdisciplinary-only counterfactual, the utilities of the programs in each applicant's program choice set are higher. This is consistent with applicants in all demographic cells preferring the Humanities and Interdisciplinary theme to others, on average. The demographic groups with the strongest relative Humanities and Interdisciplinary preferences see the largest mean increase in choice set program utility. As expected with an increase in program utilities, applicants rank more programs on average (Figure A3b), as more programs are "worth" ranking relative to the marginal application cost. Applicant subgroups with larger increases in list length in the counterfactual also see a lower rate of not receiving a main round offer in the counterfactual, relative to the baseline (Figure A3c). Black applicants, whose list lengths remain relatively unchanged in the counterfactual relative to the baseline, experience higher rates of unassignment in the counterfactual (Figure A3c).

In the counterfactual, applicants act as if all programs are Humanities and Interdisciplinary programs. Since programs are not differentiated by theme in this counterfactual, I expect to see applicants applying to a broader set of programs across baseline theme. The median applicant applies to 3 distinct themes in the baseline and the simulated baseline, and programs from 4 distinct baseline themes in the counterfactual (where the "baseline theme" of a program in the counterfactual refers to its theme in the baseline).

Application behavior overall is fairly similar in the counterfactual simulation to the baseline simulation. Of the programs ranked by each applicant in the counterfactual simulation, 87 percent were also ranked by that applicant in the baseline simulation, and 46 percent were ranked by that applicant in the baseline simulation in the same slot. 71 percent ultimately enrolled at the same program in the baseline and counterfactual simulation.

Appendix Tables

Table A1: Residential Segregation in New York City High Schools

Group	City Share HS Applicants	Segregation Indices, Relative to City Population		
		Borough SI	Subdistrict SI	Census Tract SI
Asian	0.19	0.07	0.17	0.27
Black	0.26	0.04	0.29	0.34
Hispanic	0.39	0.08	0.21	0.24
White	0.16	0.10	0.18	0.32
Not Poor	0.29	0.03	0.06	0.13
Poor	0.71	0.02	0.04	0.07
High Ach.	0.39	0.03	0.07	0.09
Non-High Ach.	0.61	0.03	0.06	0.08

Notes: The first column presents the share of the model estimation applicant sample in each demographic group. The next three columns show residential segregation indices for the high school applicant population. Residential geographic unit indices are computed according to 1, with same-group exposure computed within-cohort, and the mean taken over students in all years of the sample.

Table A2: School and Program Segregation in New York City High Schools

Group	City Share HS Applicants	Segregation Indices, Relative to City Population			
		Assigned School SI	School SI	Assigned Program SI	Program SI
Asian	0.19	0.22	0.26	0.25	0.29
Black	0.26	0.25	0.27	0.27	0.27
Hispanic	0.39	0.22	0.23	0.23	0.24
White	0.16	0.26	0.23	0.28	0.24
Not Poor	0.29	0.11	0.09	0.12	0.09
Poor	0.71	0.06	0.07	0.07	0.08
High Ach.	0.39	0.28	0.29	0.33	0.33
Non-High Ach.	0.61	0.20	0.22	0.24	0.25

Notes: The first column presents the share of the model estimation applicant sample in each demographic group. The next two columns show school segregation indices for the high school applicant population, for assigned school and enrolled school. The final two columns show program segregation indices, for assigned program and enrolled program. In all cases, the reference population is the city applicant population. School and program segregation indices are computed according to 1, with same-group exposure computed within-cohort, and the mean taken over students in all years of the sample. Note that we do not observe enrolled program, but infer it from the final program assignment and whether the student enrolls in-district. Also note that School SI and Program SI, which account for enrollment decisions, does not reflect the same-group exposure experienced by students who leave the district, since we do not know the demographics of the program/school in which they enroll.

Table A3: Other Parameter Estimates: Taste Shock Variance, Marginal Cost Mean, and Marginal Cost Variance

Taste shock variance σ_ϵ	**Marginal cost mean** c	**Marginal cost variance** σ_ζ
7.329041	0.008879	0.000043
(0.016837)	(0.000018)	(0.000000)

Notes: Estimates for taste shock variance, marginal cost mean, and marginal cost variance. Standard errors in parentheses.

Table A4: All Theme Preference Coefficient $\alpha_{cell,theme}$ Estimates

Cell	**Arts and Design**	**Business, Hospitality, and Services**	**Computing and Engineering**	**Media**	**Military and Law Enforcement**	**Multicultural**	**Public Service, Law, and Social Justice**	**Science**
Asian, non-low-income, high achievement	-2.97	-1.55	0.23	-1.64	-5.79	-2.56	-1.44	-0.08
	(0.17)	(0.15)	(0.13)	(0.30)	(0.49)	(0.34)	(0.13)	(0.16)
Asian, non-low-income, non-high achievement	-2.53	-0.94	-0.25	-1.24	-3.70	0.77	-0.97	-0.02
	(0.21)	(0.30)	(0.18)	(0.24)	(0.62)	(0.18)	(0.22)	(0.16)
Asian, low-income, high achievement	-3.00	-0.77	0.31	-1.66	-4.83	-0.45	-1.21	0.55
	(0.10)	(0.09)	(0.09)	(0.23)	(0.22)	(0.16)	(0.19)	(0.07)
Asian, low-income, non-high achievement	-2.71	-0.59	0.01	-1.27	-3.34	0.72	-0.91	0.16
	(0.09)	(0.08)	(0.07)	(0.17)	(0.20)	(0.09)	(0.17)	(0.06)
Black, non-low-income, high achievement	-1.30	-1.07	-0.52	-0.89	-4.95	-1.49	-0.36	0.34
	(0.13)	(0.14)	(0.18)	(0.25)	(0.32)	(0.31)	(0.18)	(0.11)
Black, non-low-income, non-high achievement	-0.98	-0.61	-0.22	-0.75	-1.88	-0.83	-0.06	0.11
	(0.06)	(0.10)	(0.08)	(0.14)	(0.13)	(0.12)	(0.11)	(0.07)
Black, low-income, high achievement	-1.12	-1.18	-0.07	-0.92	-2.38	-1.22	0.08	0.70
	(0.11)	(0.19)	(0.08)	(0.26)	(0.18)	(0.15)	(0.08)	(0.07)
Black, low-income, non-high achievement	-0.74	-0.33	-0.15	-0.66	-1.00	-0.80	0.16	0.28
	(0.04)	(0.04)	(0.05)	(0.06)	(0.14)	(0.07)	(0.04)	(0.03)
Hispanic, non-low-income, high achievement	-1.23	-0.79	-0.50	-1.17	-4.12	-1.12	-0.54	0.12
	(0.14)	(0.23)	(0.13)	(0.24)	(0.37)	(0.28)	(0.17)	(0.11)
Hispanic, non-low-income, non-high achievement	-1.12	-0.61	-0.39	-0.67	-2.55	-0.28	-0.25	-0.50
	(0.06)	(0.09)	(0.06)	(0.08)	(0.14)	(0.08)	(0.07)	(0.08)
Hispanic, low-income, high achievement	-1.37	-0.70	-0.34	-1.14	-3.17	-0.76	-0.48	0.01
	(0.06)	(0.06)	(0.07)	(0.15)	(0.14)	(0.09)	(0.07)	(0.08)
Hispanic, low-income, non-high achievement	-1.19	-0.49	-0.39	-0.79	-1.57	-0.27	-0.18	-0.18
	(0.05)	(0.03)	(0.03)	(0.05)	(0.09)	(0.05)	(0.03)	(0.03)
White, non-low-income, high achievement	-1.72	-1.78	-0.40	-0.82	-5.72	-1.90	-1.26	-0.33
	(0.16)	(0.32)	(0.17)	(0.17)	(0.41)	(0.28)	(0.19)	(0.09)
White, non-low-income, non-high achievement	-2.04	-0.83	-0.84	-0.72	-4.85	-1.12	-1.25	-0.98
	(0.12)	(0.25)	(0.20)	(0.23)	(0.49)	(0.41)	(0.14)	(0.21)
White, low-income, high achievement	-2.01	-1.40	-0.44	-0.80	-5.93	-1.01	-0.52	0.24
	(0.22)	(0.22)	(0.20)	(0.19)	(0.62)	(0.26)	(0.14)	(0.10)
White, low-income, non-high achievement	-2.00	-1.02	-0.51	-0.67	-3.96	-0.36	-0.71	-0.66
	(0.15)	(0.15)	(0.11)	(0.10)	(0.30)	(0.13)	(0.12)	(0.08)

Notes: Estimates for all theme preference coefficients for each demographic cell, relative to Humanities and Interdisciplinary. Standard errors in parentheses.

Table A5: Unobserved Theme Preference Covariance Matrix $\mathbf{\Sigma}_\gamma$ Estimates

	Arts and Design	**Business, Hospitality, and Services**	**Computing and Engineering**	**Humanities and Interdisciplinary**	**Media**	**Military and Law Enforcement**	**Multicultural**	**Public Service, Law, and Social Justice**	**Science**
Arts and Design	2.34	0.25	0.24	0.63	0.39	-3.61	-0.47	0.01	0.33
	(0.05)	(0.03)	(0.03)	(0.03)	(0.02)	(0.15)	(0.04)	(0.03)	(0.03)
Business, Hospitality, and Services	0.25	0.71	0.32	0.50	0.11	-2.55	0.02	0.29	0.40
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.10)	(0.02)	(0.01)	(0.02)
Computing and Engineering	0.24	0.32	1.15	0.53	0.18	-3.05	-0.27	0.34	0.65
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.10)	(0.02)	(0.01)	(0.02)
Humanities and Interdisciplinary	0.63	0.50	0.53	1.33	0.14	-4.21	-0.01	0.25	0.96
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.12)	(0.03)	(0.02)	(0.02)
Media	0.39	0.11	0.18	0.14	0.55	-1.47	-0.07	0.10	0.09
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.09)	(0.02)	(0.01)	(0.02)
Military and Law Enforcement	-3.61	-2.55	-3.05	-4.21	-1.47	20.05	-0.24	-1.64	-3.71
	(0.15)	(0.10)	(0.10)	(0.12)	(0.09)	(0.64)	(0.10)	(0.08)	(0.10)
Multicultural	-0.47	0.02	-0.27	-0.01	-0.07	-0.24	1.28	-0.17	-0.08
	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.10)	(0.04)	(0.02)	(0.02)
Public Service, Law, and Social Justice	0.01	0.29	0.34	0.25	0.10	-1.64	-0.17	0.53	0.34
	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.08)	(0.02)	(0.01)	(0.01)
Science	0.33	0.40	0.65	0.96	0.09	-3.71	-0.08	0.34	1.12
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.10)	(0.02)	(0.01)	(0.02)

Notes: Contains point estimates for the covariance matrix, Σ_γ, of the unobserved mean-zero theme preference vector, $\gamma_{\boldsymbol{cell(i),ms(i),t(i)}}$. Standard errors in parentheses.

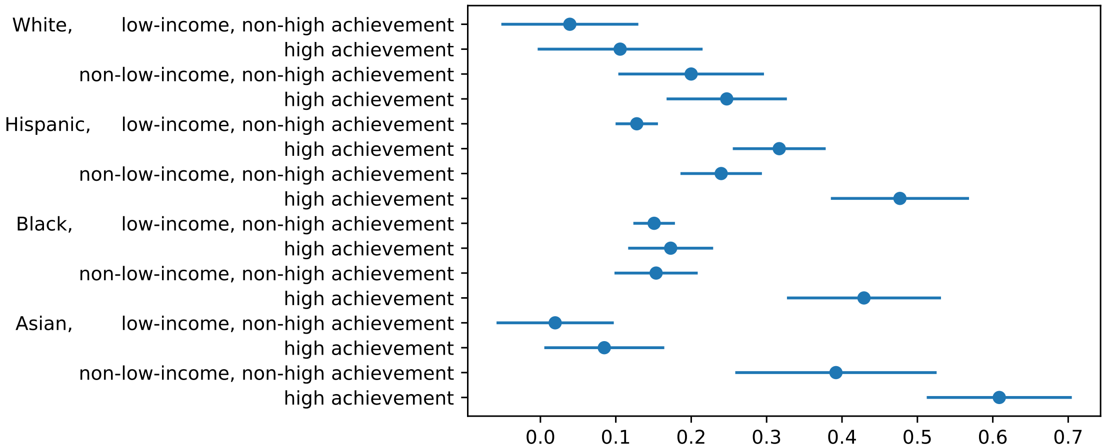
Table A6: Theme Enrollment Effects Sample Balance on Covariates

Baseline Characteristic	**F-test of joint significance p value**
Female	0.01
English Language Learner	0.34
Student with Disability	0.66
Poverty	0.26
High Achievement	0.95
Took SHSAT	0.15

Notes: I run the first stage in Equation 9 with each baseline characteristic as the outcome. I then run an F-test of joint significance of the coefficients on the theme assignment vector to determine whether theme assignment jointly having the baseline characteristic. This table displays the p-value from the F-test.

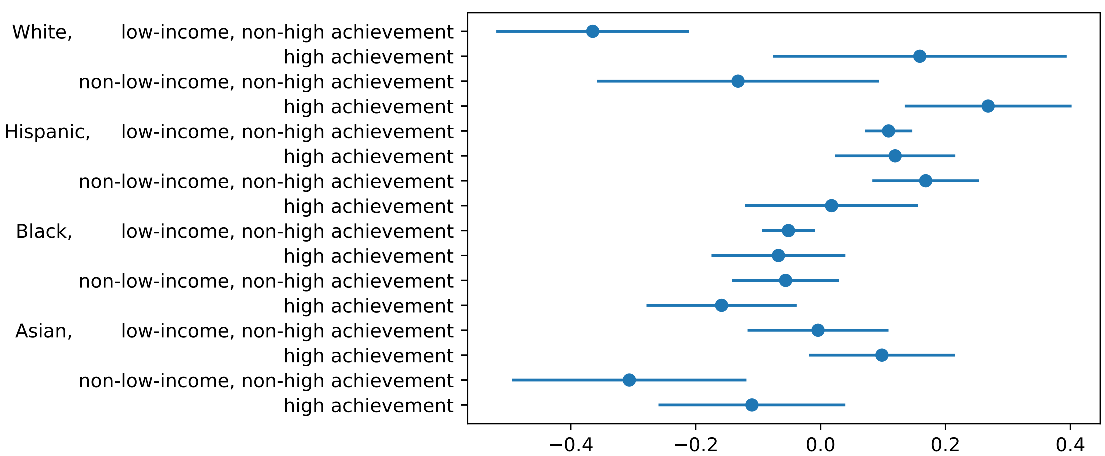
Appendix Figures

Figure A1: Preference Coefficients on Lagged Peer Characteristics $\beta_{cell,\text{ prop. high-achieving}}$



Notes: This figure shows shows 95% confidence intervals for the coefficient on proportion of students assigned to the program last year who have high baseline achievement. If a program did not exist in the previous year, this value is imputed by the mean value for the program subdistrict.

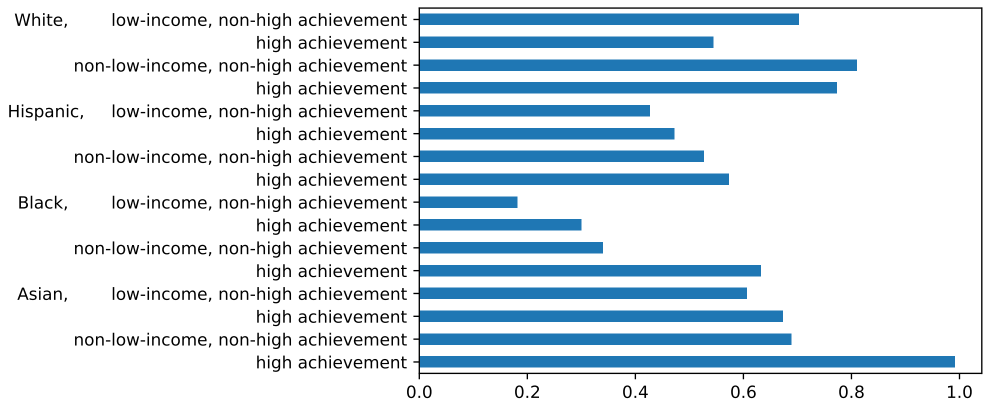
Figure A2: Preference Coefficients on Lagged Peer Characteristics $\beta_{cell,\text{ prop. same-race}}$



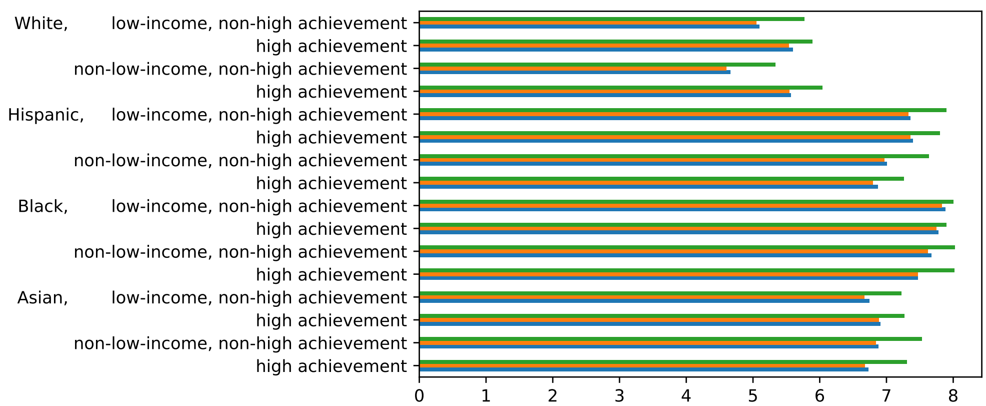
Notes: This figure shows 95% confidence intervals for the coefficient on proportion of students assigned to the program last year who are the same race as the applicant. If a program did not exist in the previous year, this value is imputed by the mean value for the program subdistrict.

Figure A3: General Application Patterns for Real Baseline, Simulated Baseline, and Simulated Counterfactual

(a) Mean change in applicant program choice set utilities, from simulated baseline to simulated counterfactual



(b) Mean list length



(c) Unassignment rate

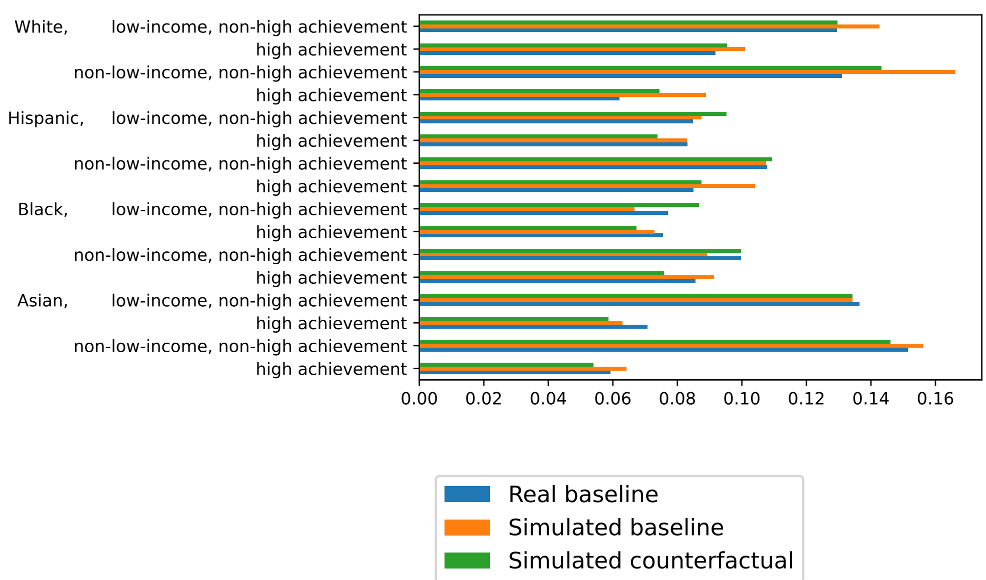
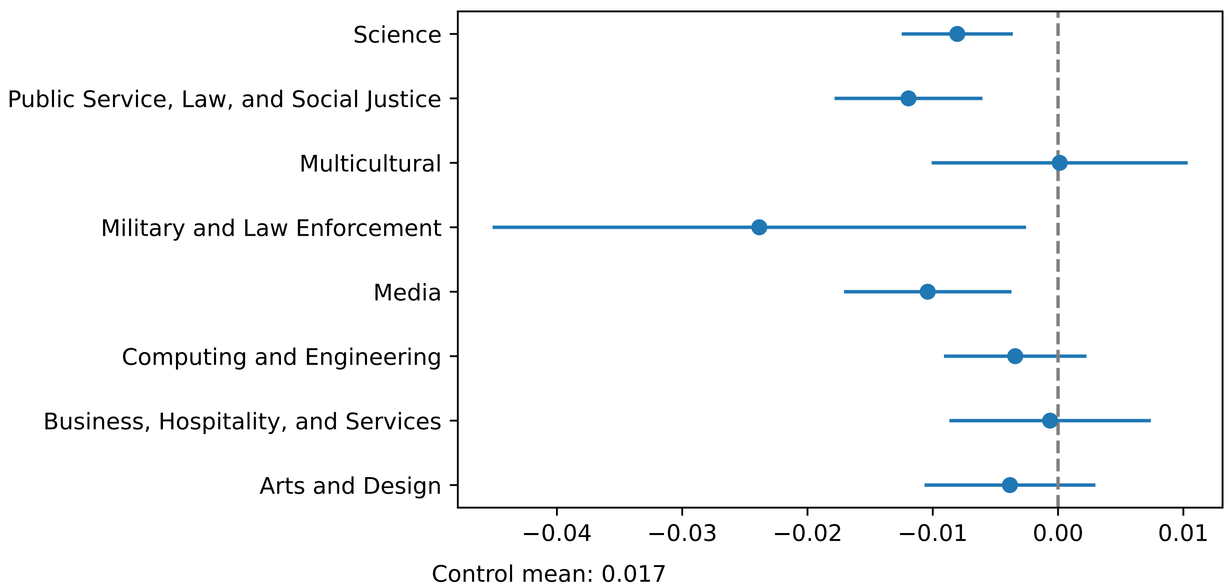
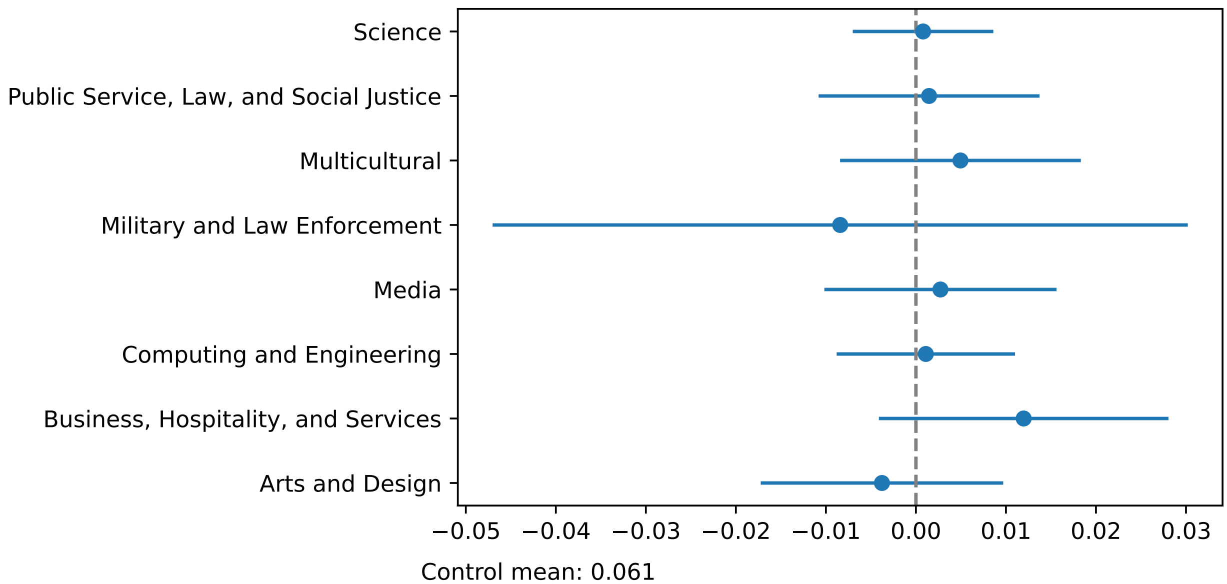


Figure A4: Effect of Theme Assignment on Missing High School Outcomes



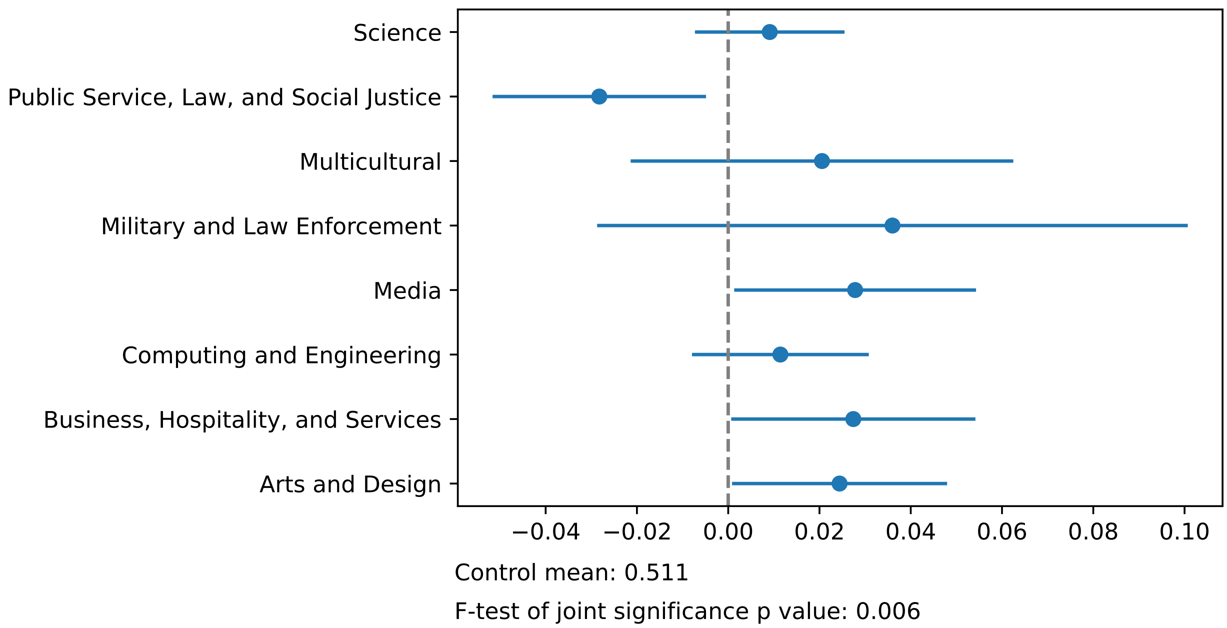
Notes: This figure plots point estimates and 95% confidence intervals for the effect of assignment to each theme on missing attendance rate, SAT taking, and high school graduation. I run the first stage in Equation 9 on the sample including applicants with missing outcomes, with an indicator of missing these outcomes as the outcome. The control mean is the proportion of Humanities and Interdisciplinary assignees with missing high school outcomes.

Figure A5: Effect of Theme Assignment on Missing Postsecondary Outcomes



Notes: This figure plots point estimates and 95% confidence intervals for the effect of assignment to each theme on missing postsecondary enrollment. I run the first stage in Equation 9 on the sample including applicants with missing postsecondary outcomes, with an indicator of missing postsecondary enrollment outcomes as the outcome. The control mean is the proportion of Humanities and Interdisciplinary assignees with missing postsecondary outcomes.

Figure A6: Proportion Female in Treatment Relative to Control Groups



Notes: I plot point estimates and 95% confidence intervals for the effect of assignment to each theme on being female, to assess balance of the estimation sample on gender. I run the first stage in Equation 9 with an indicator of being female as the outcome. The control mean is the proportion of Humanities and Interdisciplinary assignees who are female. I include the p-value from an F-test of joint significance of all plotted coefficients.