Annenberg Institute
BROWN UNIVERSITY

EdWorkingPaper No. 26-1526

The Geography of Gifted Education: Exploring School and Neighborhood Predictors of Access to Gifted & Talented Programs in New York City

Katherine Strickland
University of Florida

Wendy Chan
University of Pennsylvania

Daniel Hildreth
NYC Public Schools

Michael A. Gottfried
University of Pennsylvania

Samantha Peters
University of Pennsylvania

This study examines the community factors associated with the presence and geographic availability of Gifted and Talented (G&T) programs across New York City public schools from 2010 to 2024. Using machine learning methods (Random Forest and Classification Trees) and cross-classified multilevel logistic regression, we identify school and neighborhood characteristics associated with G&T program placement and explore how program presence varies across schools, neighborhoods, and districts. We find that most variation in G&T program presence occurs between neighborhoods rather than between districts, indicating that neighborhood context and community factors are strongly associated with where programs are located. Among neighborhood characteristics, homeownership remained positively associated with G&T presence in the fully adjusted model (OR = 1.25, p = .005), after controlling for school demographics, district membership, and measured neighborhood education, poverty, and foreign-born population share. Finally, we compare the city's 2022-2024 G&T expansion to this historical placement pattern. Expansion schools were located in higher-poverty, lowerhomeownership, and more racially diverse neighborhoods than those that historically hosted programs, indicating broader geographic availability in the expansion period.

VERSION: July 2026

Suggested citation: Strickland, Katherine, Wendy Chan, Daniel Hildreth, Michael A. Gottfried, and Samantha Peters. (2026). The Geography of Gifted Education: Exploring School and Neighborhood Predictors of Access to Gifted & Talented Programs in New York City. (EdWorkingPaper: 26-1526). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/165c-7k18

The Geography of Gifted Education: Exploring School and Neighborhood Predictors of Access to Gifted & Talented Programs in New York City

Katherine Strickland, Postdoctoral Researcher, University of Florida
Wendy Chan, Associate Professor, University of Pennsylvania
Daniel Hildreth, Senior Director of Portfolio Planning, NYC Public Schools
Michael Gottfried, Professor, University of Pennsylvania
Samantha Peters, PhD student, University of Pennsylvania

Abstract

This study examines the community factors associated with the presence and geographic availability of Gifted and Talented (G&T) programs across New York City public schools from 2010 to 2024. Using machine learning methods (Random Forest and Classification Trees) and cross-classified multilevel logistic regression, we identify school and neighborhood characteristics associated with G&T program placement and explore how program presence varies across schools, neighborhoods, and districts. We find that most variation in G&T program presence occurs between neighborhoods rather than between districts, indicating that neighborhood context and community factors are strongly associated with where programs are located. Among neighborhood characteristics, homeownership remained positively associated with G&T presence in the fully adjusted model (OR = 1.25, p = .005), after controlling for school demographics, district membership, and measured neighborhood education, poverty, and foreign-born population share. Finally, we compare the city's 2022-2024 G&T expansion to this historical placement pattern. Expansion schools were located in higher-poverty, lower-homeownership, and more racially diverse neighborhoods than those that historically hosted programs, indicating broader geographic availability in the expansion period.

Keywords: Gifted education; education policy; educational inequality; neighborhood effects; geographic access; New York City
Acknowledgements: We thank the New York City Department of Education Research and Policy Support Group for providing access to the administrative data used in this study.
Financial Disclosure: The authors received no financial support directly related to this research

I. Introduction

Gifted education programs are designed to provide academic acceleration and enrichment for students identified as high-ability learners. Research suggests that advanced academic grouping can improve outcomes for participating high-achieving students (Card & Giuliano, 2016a). Yet Black, Hispanic, and low-income students remain substantially underrepresented in gifted programs nationwide (Card & Giuliano, 2016b; Grissom, Redding, & Bleiberg, 2019; Plucker, Burroughs, & Song, 2010). Multiple factors contribute to these disparities, including identification procedures that may reinforce existing inequalities, information barriers that privilege families with greater social capital, and geographic inequities in program availability (Grissom, Redding, & Bleiberg, 2019; Lu, Weinberg, & McCormick, 2020; Peters & Carter, 2022).

Our paper focuses on this geographic dimension in the context of New York City's Gifted and Talented (G&T) program. We ask: in what types of schools, and in which neighborhoods, are G&T programs located? The availability of a program in a child's school represents what might be called the "first stage" of access. Before questions of identification or selection arise, a program must exist in the building. If it does not, families may never learn that such programs are available, and students cannot be considered for programs that are not there. This initial stage of access is where some of the most consequential sorting occurs (Sattin-Bajaj & Roda, 2020).

We examine the 2010 to 2024 period in New York City, which spans two distinct policy eras. From 2010 to 2020, G&T program locations remained largely stable, with entrenched patterns of concentration in certain schools and neighborhoods. After 2020, following critiques of inequitable access and the disruption of COVID-19, the city launched an initiative to expand G&T presence in historically underserved schools. We analyze these periods separately. First, we characterize the "historical access structure" of 2010 to 2020, identifying school and neighborhood factors associated with program presence. We use machine learning techniques (Random Forest and Classification Trees) to screen a large set of census-level predictors and identify which variables matter most. We then use cross-classified multilevel logistic regression to decompose G&T inequality across schools, neighborhoods, and districts, isolating neighborhood-level predictors from both school composition and district membership. Finally, we evaluate whether the 2022 to 2024 policy expansion altered these historical placement patterns.

This study makes three contributions. First, we demonstrate that G&T program inequality operates primarily at the neighborhood level. Our cross-classified multilevel model indicates that 63% of the variation in program placement occurs between neighborhoods, compared to just 11% between districts. This finding challenges the common approach of treating school districts as the relevant geographic unit for understanding G&T program presence. Substantial inequality exists below the district level, between neighborhoods instead. Among tract-level local-area characteristics, homeownership rates independently predict G&T presence after controlling for school demographics, district membership, and other tract-level factors including education levels and poverty rates.

Second, we assess whether NYC's 2022 to 2024 G&T expansion altered the historical placement pattern. Using predicted probabilities from the historical model, we find that 91% of schools that gained new G&T programs had less than a 10% predicted probability of hosting a program under the old patterns. These expansion schools were located in higher-poverty and lower-homeownership local contexts and served more racially diverse student populations than schools that historically hosted programs. Taken together, these patterns are consistent with broader geographic availability in the expansion period.

Third, we contribute methodologically by demonstrating how machine learning and multilevel modeling answer complementary questions about educational inequality. Machine learning methods reveal overall predictive patterns and identify key thresholds at the citywide level. Multilevel regression formally separates variation across geographic levels and provides interpretable effect estimates. By analyzing neighborhood-level variation using Neighborhood Tabulation Areas (NTAs) rather than relying solely on district-level comparisons, we show that administrative boundaries can obscure the community-level factors that shape educational opportunity (Tate, 2008; Türk & Östh, 2019).

II. Background and Context

The Geography of Opportunity

Our study is grounded in the geography of opportunity framework, which holds that a child's location fundamentally shapes their access to educational resources and their long-term outcomes (Tate, 2008). Chetty and Hendren (2018) demonstrated that childhood exposure to higher-quality neighborhoods produces lasting effects on earnings and college attendance, with each additional year of exposure generating measurable improvements. Chetty and colleagues (2020) further showed that these neighborhood effects vary by race, with Black children experiencing sharply different returns to neighborhood quality than White children raised in the same areas. Social capital, including the networks, norms, and trust that facilitate collective action within communities, also varies across neighborhoods and is independently associated with economic mobility (Chetty et al., 2022). Bergman and colleagues (2024) confirmed that these effects are not purely a product of family selection. They find that providing families with information and vouchers to move to higher-opportunity neighborhoods produced meaningful gains for their children.

Applied to education, this framework predicts that the resources available in a child's school are shaped not only by district-level policy but by the characteristics of the surrounding community. Green, Sánchez, and Germain (2017) showed that school quality ratings cluster geographically even within the same district, creating distinct zones of educational advantage and disadvantage. Türk and Östh (2019), using Swedish longitudinal data and multilevel regression, found that neighborhood characteristics predict long-term outcomes for children even after accounting for individual and family factors. Corcoran and Baker-Smith (2018) documented an extreme version of this pattern in New York City, finding that 50% of students admitted to specialized high schools originated from just 5% of middle schools. The concentration of access to elite educational pathways reflects systematic differences in school-level resources and preparation that vary sharply across neighborhoods.

We extend this framework to the specific question of where gifted education programs are located. G&T programs represent a concrete educational resource whose geographic distribution is not random but is closely associated with neighborhood characteristics. Because race, socioeconomic status, and geography are deeply intertwined in American cities (Chetty et al., 2020; Mordechay & Ayscue, 2024), geographic disparities in program availability may translate into demographic disparities in access.

Research on Access to Gifted Programs

Research on gifted education disparities has addressed barriers at multiple stages of access. One body of work examines identification, meaning how students are recognized and selected for programs. Standardized testing, teacher nominations, and other selection procedures have each been shown to contain potential biases that disadvantage low-income students and students of color (Ford, Wright, & Trotman Scott, 2020; Hines et al., 2022; Peters, 2022). Grissom, Redding, and Bleiberg (2019) documented that socioeconomic gaps in receipt of gifted services persist even among students with comparable achievement. Dixson and colleagues (2025) argue that these patterns are a product of how gifted education is organized structurally, not simply through individual biases among teachers or test designers. Information asymmetries can also compound these identification barriers. Lu, Weinberg, and McCormick (2020) found that attending public pre-Kindergarten increased G&T test-taking rates, particularly among immigrant families and those receiving free lunch, suggesting that institutional connections serve as information pipelines that facilitate or hinder access.

Reform efforts targeting identification have shown promise. Universal screening, in which all students are evaluated regardless of family initiative, substantially increased identification rates among economically disadvantaged students in a Florida district without changing eligibility criteria (Card & Giuliano, 2016b). Local norms approaches, which benchmark student performance against peers in similar contexts rather than national standards, have also improved representation (Peters et al., 2019). Plucker, Wells, and Meyer (2022) advocate for comprehensive policy redesign that addresses both identification and access. Yeung and Mun (2022) emphasize the importance of disaggregating racial and ethnic data to reveal variation that broad demographic categories can mask.

A second body of work examines the availability of programs themselves, meaning where they are located and which schools and communities have access. Yaluma and Tyner (2021) documented that gifted programs are significantly less common in high-poverty schools nationally. Peters and Carter (2022) identified school-level characteristics that predict access to gifted services. Our study contributes to this strand of research by examining neighborhood-level factors and the geographic structure of program availability within a single urban district, and by evaluating whether a deliberate policy expansion can alter entrenched placement patterns.

Most policy efforts to broaden gifted access have focused on identification rather than location. These reforms include universal screening (Card & Giuliano, 2016b), changes in testing instruments or norms (Carman et al., 2018), teacher rating scales designed to surface talent among low-income students (Peters & Gentry, 2010), and multiple-measure systems intended to expand the pool of academically advanced students from underserved groups (Tran et al., 2022). A separate, less-studied strategy is to expand the geographic footprint of gifted programs themselves. Rather than changing who can qualify for a fixed set of sites, this supply-side approach changes where programs are located and therefore which communities encounter them as a realistic option. New York City's 2022-2024 expansion provides a useful case for examining that strategy in practice.

NYC School Districts and Neighborhoods

New York City operates one of the largest public school systems in the United States, enrolling over one million students across more than 1,800 schools in 32 community school districts spanning five boroughs. The system encompasses substantial demographic, economic, and geographic diversity. School and neighborhood characteristics vary dramatically even within short distances, making NYC a particularly informative setting for studying the geography of educational opportunity.

The city's 32 community school districts are administrative units, each governed by a superintendent and community school board, and their boundaries are political constructions with their own histories rather than reflections of how residents experience neighborhood space

(Kafka & Matheny, 2021). A typical district contains roughly nine distinct neighborhoods, and within-district variation in residential composition, homeownership, income, and other community characteristics is considerable. Two neighborhoods governed by the same superintendent can differ sharply in the resources and programs available to their schools. District-level comparisons can therefore mask much of the local variation that shapes educational opportunity. Throughout this paper, we accordingly treat the neighborhood, rather than the district, as the more informative geographic unit for understanding where G&T programs are located. We describe how we operationalize neighborhoods in the Data and Methods section.

NYC Gifted and Talented

NYC's G&T program has been a subject of public debate for decades. Formalized gifted education in the city dates to the 1970s, and questions of who benefits and who is excluded have accompanied the program throughout its history. In 2008, the city centralized G&T admissions around a standardized testing process using the OLSAT and NNAT assessments. Students scoring at or above the 90th percentile could apply to district-level programs, and those at the 97th percentile or above were eligible for citywide programs.

The centralized admissions process did not, however, produce an even distribution of programs. G&T classrooms were concentrated in certain districts and neighborhoods while largely absent from others. Some Manhattan districts maintained dozens of G&T classrooms, while districts in the South Bronx operated only a handful. The admissions process gave priority to students applying within their home district, which meant that a student's neighborhood effectively determined both whether a program was available nearby and their realistic chances of obtaining a seat. Geographic disparities in program availability thus reinforced the socioeconomic and racial disparities in G&T participation that the centralized process was intended to address.

The COVID-19 pandemic disrupted the admissions process entirely. Testing was suspended during the 2020 to 2021 school year. For the 2021 to 2022 school year, pre-K teachers could nominate students based on classroom observations rather than standardized test performance. The following year, the city implemented what it described as universal screening, making all students eligible for consideration regardless of whether their families had applied.

The Expansion Period[1]

The pandemic-era disruption coincided with another policy change. In late 2021, the outgoing de Blasio administration announced plans to phase out the G&T program and replace it with a new one. After taking office in January 2022, Mayor Eric Adams instead adopted an expansion approach, emphasizing increased geographic availability rather than program elimination. The new administration would specifically target G&T program expansion to districts that had never offered the program before. The new citywide commitment was to establish at least one kindergarten-entry and one grade 3-entry program in every district. In some districts, implementation went beyond that minimum, producing multiple new sites in fall 2022.

This shift reframed the issue less as one of student deficits and more as one of site availability. Prior to the expansion, one common explanation for neighborhoods without G&T programs was that too few students there met the earlier eligibility standard. Once the admissions process changed, that explanation became less persuasive, creating space for a different approach to site placement. More broadly, the expansion challenged the long-standing “chicken or egg”

[1] This section draws in part on institutional knowledge from a coauthor who worked in NYC Public Schools during the 2022-24 G&T expansion period. We include this material to provide implementation context for the policy changes analyzed below.

logic of G&T placement: should programs be located only where large numbers of already-identified students exist, or can the placement of a program itself generate demand and participation? In practice, the expansion reflected the latter view by placing programs first in previously underserved areas and allowing demand to develop around them.

To achieve this expansion goal, central NYC Public Schools teams worked directly with superintendents to identify where these programs should be located in the districts they oversee. In principle, the process was meant to account for instructional fit, principal willingness, and local context, but practical capacity constraints were often decisive. A school might have appeared to be a strong fit based on community perception, leadership quality, and instructional approach, yet still lack the space needed to sustain a program at scale. In general, superintendents preferred willing principals, but in practice the feasible set of sites was often narrower than the ideal set. This led to some programs placed in schools whose leadership was ideologically opposed to the program from an equity or instructional perspective.

A related challenge in G&T program planning is that some programs may be the only viable option in a given neighborhood but may still struggle to fill their seats at levels that make them financially sustainable. Because these programs represent the only local option across broad geographic areas, proposals to close or consolidate them can generate substantial political resistance, particularly in communities with few alternatives. As a result, some low-enrollment programs may persist even when they are operationally difficult to sustain.

Maintaining these programs with very small enrollment rates can also be operationally difficult for schools. A class with just a handful of students is, as mentioned earlier, financially unworkable. At the same time, if the school programs these students into a general education class, G&T instruction becomes a differentiated approach within a general education setting rather than a distinct class. As families become aware of this dynamic, either having their child enrolled in a class that is very small or accepting that the G&T instruction will not take place in a distinct classroom for the G&T students, the program's reputation and desirability may diminish.

As G&T programs have expanded to areas that previously had few or none, the pressure put on individual programs seems to have lessened in the sense that district superintendents and principals have successfully phased out programs without much pushback from the community since there are now typically multiple programs in each district. This may not have been possible in prior years because of the limited nature of the program. Today, the system can mean many different things to many different people. With the mix of program models (district and citywide), entry points (kindergarten and grade 3), and variety of approaches toward implementation, it is very difficult to say with any degree of certainty what is truly consistent across all these programs.

III. Data & Methods

Research Questions

We address two main research questions:

RQ1: What school demographic and neighborhood characteristics are associated with the presence of G&T programs during the historical period (2010-2020), and at what level (school, neighborhood, district) does the most variation in G&T access occur?

RQ2: Did the 2022-2024 expansion reach schools and neighborhoods with different characteristics than those that historically hosted G&T programs?

Data Sources

We construct a school-year panel dataset covering all New York City public schools from 2010-11 through 2023-24 (14 academic years). Student-level administrative records were obtained from the NYC Department of Education, providing enrollment, demographic characteristics, and gifted identification status for each student. These records were aggregated to the school-year level, yielding approximately 1,600 schools observed annually. Schools in Districts 75 and 79 (special education and alternative programs) were excluded.

Local-area characteristics were drawn from American Community Survey 5-year estimates obtained through the Census Bureau API using the tidycensus R package. We downloaded census-tract data for the five New York City counties for ACS vintages 2015 through 2022. Schools were linked spatially to the census tract containing the school building, and each school-year was assigned the ACS values for that tract and the appropriate ACS vintage. School years 2010-11 through 2014-15 were matched to the 2015 ACS vintage, and 2023-24 was matched to the 2022 vintage. These tract-level measures represent the immediate local context surrounding each school.

Measures

Outcome. Our outcome is a binary indicator of whether a school had a G&T program in a given year, defined as enrolling 10 or more G&T-identified students. This threshold was chosen to distinguish schools with established programs from those with only a handful of individually-identified gifted students.

School-level predictors. We included eight school-level demographic measures: total enrollment, percent Black, percent Hispanic, percent White, percent Asian, percent eligible for free or reduced-price lunch (our poverty measure), percent English Language Learners (ELL), and percent Students with Disabilities (SWD). For schools with G&T programs, school-level demographics were computed excluding G&T-identified students (i.e., using the general education population only).

Tract-level local-area predictors. We included 27 ACS measures for the census tract containing each school, covering income, employment, housing tenure and costs, housing structure, education, family structure, nativity, and residential stability. These measures vary over time through the matched ACS vintage and are interpreted as characteristics of the school's immediate local context.

Analytical Approach

Our analysis proceeds in three stages. In Stage 1, we use machine learning methods to characterize the historical access structure governing G&T program placement citywide. In Stage 2, we use cross-classified multilevel logistic regression to compare clustering at the NTA and district levels and to estimate associations between tract-level ACS characteristics and G&T program presence after accounting for school composition and geographic clustering. In Stage 3, we descriptively compare the schools that gained G&T programs during 2022-2024 with schools that hosted programs in both the historical and expansion periods.

Districts vs. Neighborhoods

A key feature of our analytical framework is the distinction between school districts and neighborhoods. New York City's 32 school districts are administrative boundaries, each governed by a superintendent and community school board. A single district typically contains multiple neighborhoods, captured by Neighborhood Tabulation Areas (NTAs). On average, each district contains approximately 9 NTAs and there is considerable within-district variation in residential composition, homeownership, income, and other community characteristics between NTAs.

ACS covariates are measured at the census-tract level, the most granular geography available from the American Community Survey. Because many tracts contain only one or two schools, they are too small to serve as the grouping level for random intercepts. We therefore retain each school's own tract-level ACS values but use Neighborhood Tabulation Areas (NTAs) as the broader neighborhood grouping in the multilevel models. NTAs aggregate tracts into recognizable neighborhood areas, allowing Stage 1 to model citywide patterns using tract measures and Stage 2 to compare clustering at the NTA and district levels.

Stage 1: Machine Learning for Variable Selection

We used Random Forest and CART to identify citywide predictors of G&T program placement during the historical period (2010-11 through 2019-20), using a pooled complete-case panel of approximately 13,000 school-years and 35 predictors (8 school-level, 27 tract-level ACS measures). Stage 1 describes the citywide predictive structure and informs which local-area predictors enter the multilevel models in Stage 2.

Random Forest. We fit a 500-tree classifier with class weights upweighting G&T schools by a factor of 10 to address class imbalance (More & Rana, 2017). Variable importance was measured by mean decrease in accuracy, with larger values indicating a greater contribution to out-of-bag prediction.

Classification and Regression Trees (CART). We fit a recursive partitioning model with equal class priors and pruned the initial tree using the 1-SE rule (Breiman et al., 1984) to favor parsimony. CART provides interpretable splitting rules and variable-importance scores based on total reduction in the splitting criterion.

Cross-method comparison. We compared variable importance rankings across RF and CART and identified predictors that ranked highly in both. We also examined pairwise correlations among the tract-level ACS predictors and flagged pairs with absolute correlations above 0.7 before selecting local-area variables for Stage 2.

Stage 2: Cross-Classified Multilevel Logistic Regression

To decompose G&T inequality across levels and test whether tract-level local-area characteristics predict G&T presence net of school composition and district membership, we estimated cross-classified multilevel logistic regression models (Raudenbush & Bryk, 2002; Bates et al., 2015). Schools are cross-classified by NTA and district (rather than nested), because NTA boundaries do not align with district boundaries (some NTAs span multiple districts).

Our model does not include a school-level random intercept. G&T program status is highly stable within schools across years, leaving insufficient within-school variation to support a third variance component. We tested this in preliminary models that included a school random intercept and the estimated variance collapsed to zero (singular fit).

Model specification.

The general specification is:

$$\text{logit}\big[\Pr\big(Y_{ijk}=1\big)\big]=\beta_0+\boldsymbol{X}_{ijk}\boldsymbol{\beta}+\boldsymbol{Z}_j\boldsymbol{\gamma}+u_j+v_k$$

where Y_{ijk} indicates whether school i in neighborhood j and district k hosted a G&T program, $\boldsymbol{X}_{ijk}$ is the vector of school-level predictors, $\boldsymbol{Z}_j$ is the vector of tract-level predictors, and u_j and v_k are random intercepts for neighborhood and district, respectively:

$$u_j \sim \mathcal{N}(0,\sigma_u^2), \qquad v_k \sim \mathcal{N}(0,\sigma_v^2)$$

All continuous predictors were standardized prior to estimation. The model does not include a school-level random intercept because G&T program status is highly stable within schools across years.

Model Sequence

We estimated four nested specifications in Stage 2.

Model 0 (M0): Empty model

$$\text{logit}\left[\Pr\left(Y_{ijk} = 1\right)\right] = \beta_0 + u_j + v_k$$

Model 1 (M1): School-level predictors

$$\text{logit}\left[\Pr\left(Y_{ijk} = 1\right)\right] = \beta_0 + \boldsymbol{X}_{ijk}\boldsymbol{\beta} + u_j + v_k$$

Model 2 (M2): Adds the focal tract-level predictor

$$\text{logit}\left[\Pr\left(Y_{ijk} = 1\right)\right] = \beta_0 + \boldsymbol{X}_{ijk}\boldsymbol{\beta} + \gamma_1 H_j + u_j + v_k$$

Model 3 (M3): Adds additional tract-level controls

$$\text{logit}\left[\Pr\left(Y_{ijk} = 1\right)\right] = \beta_0 + \boldsymbol{X}_{ijk}\boldsymbol{\beta} + \gamma_1 H_j + \gamma_2 G_j + \gamma_3 P_j + \gamma_4 F_j + u_j + v_k$$

In this sequence, H_j denotes percent owner-occupied housing, G_j denotes percent of neighborhood residents with a graduate degree, P_j denotes neighborhood poverty rate, and F_j denotes percent foreign-born.

Variance decomposition. We quantify the relative contribution of neighborhoods and districts to G&T program placement using latent-variable intraclass correlation coefficients (ICCs) for the cross-classified logistic models (Snijders & Bosker, 2012):

$$\rho_N = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2 + \pi^2/3}, \qquad \rho_D = \frac{\sigma_v^2}{\sigma_u^2 + \sigma_v^2 + \pi^2/3}$$

Here, ρ_N denotes the share of total latent variance attributable to neighborhoods and ρ_D denotes the share attributable to districts. When $\rho_N > \rho_D$, variation in G&T program presence is more strongly structured across neighborhoods within districts than across districts themselves.

Robustness. Our primary multilevel models pool school-year observations from 2010-11 through 2019-20 to describe the historical placement pattern. Because the same schools appear in multiple years and the model does not include a school random intercept, the NTA and district random effects do not account for all within-school dependence. The pooled ICCs should therefore be interpreted as latent variance shares for the pooled school-year specification rather than as design-invariant quantities. We assess robustness in five ways. First, we estimate the model on the 2019-20 cross-section, which removes repeated school observations. Second, we estimate the homeownership model separately in each historical year. Third, we use the City-Defined Neighborhood Dataset rather than NTAs. Fourth, we vary the G&T threshold from the main 10-student definition to 5 and 15 students. Fifth, we restrict the sample to schools serving plausible elementary entry grades based on the NYC school location file. We focus on whether the direction and substantive ordering of results persist across these checks, rather than expecting identical ICC magnitudes across specifications.

Stage 3: Descriptive Assessment of Expansion Placement

To describe whether the 2022-2024 expansion reached a different set of schools, we classified schools into four trajectory groups based on G&T status during the historical period (2010-2020) and the expansion period (2022-2024). The COVID suspension years, 2020-21 and 2021-22, were excluded. Our primary comparison is between Historical and Expansion G&T schools, which hosted programs in both periods, and Gained G&T schools, which first hosted programs during 2022-24. We also identify Lost G&T and Never G&T schools. Table A4 reports the trajectory counts, and Table A6 compares observed 2019-20 school and local-area characteristics across the groups.

As a supplementary descriptive exercise, we applied Model 1 to 2019-20 school characteristics and compared the distribution of conditional fitted probabilities across trajectory groups. These fitted values include the estimated NTA and district random intercepts and therefore summarize how closely each school resembled the historical placement pattern represented by the model. They are not out-of-sample forecasts, and they are not used to estimate a causal policy effect. The primary evidence for Stage 3 is the observed comparison of trajectory groups in Tables A4 and A6.

IV. Results

Descriptive Patterns

Table 1 presents the number and percentage of schools with G&T programs by year and borough from 2010 to 2024. In 2010-11, 115 schools citywide (6.8%) hosted G&T programs. This number declined gradually over the historical period, reaching 96 schools (5.7%) by 2019-20. The decline was concentrated in Brooklyn, which fell from 49 G&T schools (9.3%) to 30 (5.8%) over this period. The Bronx consistently had the fewest G&T schools, with no more than 10 in any year and rates ranging from 1.4% to 2.6%. Queens and Staten Island maintained relatively stable counts throughout the decade. Table 2 complements these trends by comparing 2019-20 G&T and non-G&T school characteristics within each borough, showing that G&T schools were typically larger and socioeconomically more advantaged than non-G&T schools.

Figure 1 displays these trends visually across boroughs. Panel A shows the percentage of schools with G&T programs, Panel B shows the number of schools with G&T programs, and Panel C shows total G&T students. Two features of the trend are notable. First, the COVID-19 suspension period (2020-21 and 2021-22) produced a visible dip in G&T counts across all boroughs. Second, beginning in 2022-23, a sharp increase is evident: the citywide total rose to 124 schools (7.3%), the highest point in the study period. This increase was driven by gains in the Bronx, Brooklyn, and Queens.

Figure 2 shows neighborhood-level change between 2019-20 and 2022-23. Gains are concentrated in parts of the Bronx, central Brooklyn, and Queens that had little or no prior G&T presence, while losses are fewer and more spatially limited. The map makes clear that the post-

2022 expansion did not simply deepen the existing footprint in historically advantaged areas; it also extended programs into a broader set of neighborhoods.

Figure 2 also underscores that the expansion was not spatially uniform. In the South Bronx and in more peripheral parts of Queens and Brooklyn, including the Rockaways, new programs often appeared in neighborhoods that previously had little or no G&T presence, effectively filling gaps in the historical footprint. By contrast, lower Manhattan and Staten Island changed much less. In Staten Island, this relative stability is consistent with a borough structure in which the more affluent South Shore already had an established G&T presence but limited room for further expansion, while less affluent North Shore neighborhoods had more physical capacity but historically weaker program presence. The result is a borough where the post-2022 period largely preserved an existing uneven distribution rather than creating a new one.

These descriptive patterns establish that G&T programs are not distributed randomly across schools or neighborhoods. They are concentrated in schools with specific demographic profiles and in neighborhoods with specific socioeconomic characteristics. The analytical stages that follow examine which of these factors predict G&T presence and at what geographic level the inequality operates.

Stage 1: Machine Learning - What Predicts G&T Citywide?

Table A5 reports variable importance rankings from both models. Three variables appear in the top 10 of both methods: total enrollment (ranked 1st in both), percent White (8th in RF, 3rd in CART), and percent of households earning $200,000 or more (4th in both). School enrollment is the dominant predictor, accounting for 20.2% of the total reduction in the CART splitting criterion and producing the largest mean decrease in accuracy in the Random Forest.

The CART tree reveals threshold effects. Schools with enrollment below approximately 500 have very low predicted probabilities of hosting a G&T program. Among larger schools, subsequent splits involve percent White, tract-level income, and percent married-couple families. Tract-level variables appear at multiple points in the tree alongside school-level variables, which indicates that local context adds predictive information beyond school composition alone.

The key finding from Stage 1 is that school composition dominates citywide prediction, but tract-level local-area characteristics (income, family structure, professional occupation, homeownership) contribute independently. These results informed which broader local-area dimensions we carried into the multilevel models. Homeownership ranks 16th in both methods, which is consistent with our use of it as a theoretically motivated focal predictor rather than as the single strongest citywide screening variable. Its contribution becomes clearer in Stage 2, which conditions on district and neighborhood structure.

Stage 2: Multilevel Models

Table 3 presents the variance decomposition from the cross-classified multilevel models. The empty model (M0) attributes 63% of the total variation in G&T program placement to differences between Neighborhood Tabulation Areas (NTAs), 11% to differences between districts, and the remaining 27% to residual within-neighborhood variation. Because the model does not include a school random effect, this final component should be interpreted as within-neighborhood residual variation rather than as a pure between-school share.

Table 4 reports the fixed-effect estimates from the model sequence. In M1, which includes only school-level demographics, enrollment is positively associated with G&T presence (OR = 1.17, $p < .001$) and percent students with disabilities is also positively associated (OR = 1.23, $p < .001$). None of the four racial composition variables reach statistical significance once

NTA and district random intercepts are included. School-level poverty is also nonsignificant (OR = 0.94, $p = .30$).

M2 adds a single tract-level predictor: percent owner-occupied housing. Homeownership is positively and significantly associated with G&T presence (OR = 1.31, $p < .001$). M3 adds three additional tract-level predictors (percent with a graduate degree, percent in poverty, and percent foreign-born), and homeownership remains significant (OR = 1.25, $p = .005$), indicating that its association with G&T presence is not reducible to local educational attainment or income. Tract poverty is negatively associated with G&T presence (OR = 0.62, $p < .001$). Percent foreign-born is positively associated (OR = 1.69, $p < .001$). Percent with a graduate degree is not significant (OR = 1.11, $p = .26$). The AIC decreases from 5,832 in M1 to 5,815 in M2 to 5,740 in M3 (Table A3), indicating improved fit with each additional specification.

These findings are robust to reasonable alternative coding choices. In supplementary analyses reported in Appendix Table A10, varying the threshold used to classify a school as offering G&T from 5 to 15 students yields very similar fully adjusted M3 estimates for tract-level homeownership in the pooled models. Restricting the historical sample to schools serving plausible elementary entry grades also yields substantively similar estimates.

Appendix Table A7 illustrates these patterns with concrete within-district examples. Within District 2 (Manhattan), Upper East Side-Carnegie Hill had G&T programs in 66.7% of schools and 57.5% owner-occupied housing, while Chinatown had G&T programs in 6.2% of schools and 9.4% owner-occupied housing. In District 13, Prospect Heights had G&T programs in 100% of schools, compared with 0% in Bedford. In District 20, Bath Beach had G&T programs in 50% of schools and 47.1% owner-occupied housing, while Sunset Park East and

Sunset Park West had no G&T programs and 22.8% owner-occupied housing. These examples illustrate that substantial neighborhood variation in G&T access exists within the same district.

As a first robustness check, we re-estimated the Stage 2 models on a single 2019-20 cross-section, eliminating repeated school observations. In that single-year specification, the neighborhood ICC still exceeded the district ICC (7.2% vs. 2.9%). Homeownership remained positive in both M2 and M3 (OR = 1.35, $p = .010$; OR = 1.24, $p = .145$), although the fully adjusted single-year estimate was less precise. We also estimated the homeownership model (M2) separately for each of the 10 historical cross-sections from 2010-11 through 2019-20 (Table A8). The coefficient is positive in all 10 years and statistically significant at the .05 level in 8 of 10, with odds ratios ranging from 1.18 to 1.40. These results suggest that the pooled panel sharpens precision but does not create the basic neighborhood pattern.

We also re-estimated the Stage 2 models using the City-Defined Neighborhood Dataset (CDND) rather than NTAs. CDND is substantially coarser in our sample (59 polygons versus 187 NTAs), but the broad variance decomposition result holds. Neighborhood-level clustering is larger than district-level clustering in the empty model under both definitions, and school racial composition remains non-significant in the full model under both specifications. The homeownership coefficient remains positive but becomes imprecise under CDND, which suggests that the strongest neighborhood sorting signal may operate at a finer geography than the coarser city-defined polygons capture. Appendix Table A10 likewise shows that the fully adjusted M3 homeownership estimate is robust to redefining G&T program presence using 5- and 15-student cutoffs and to restricting the sample to schools serving plausible elementary entry grades. Across all six specifications, the coefficient remains positive and statistically significant.

Stage 3: Policy Evaluation

Table A4 reports the group counts. Of the 1,804 schools observed across both periods, 87 (4.8%) had G&T programs during both the historical and expansion periods (Historical and Expansion G&T). Forty-three schools (2.4%) gained G&T programs during 2022-24 that they did not have historically (Gained G&T). Sixty-two schools (3.4%) lost their G&T programs (Lost G&T), and 1,612 schools (89.4%) never had G&T programs in any year (Never G&T).

Appendix Figure 1 displays the predicted probability distributions for each group. Predicted probabilities are generated from M1 (school demographics with NTA and district random intercepts) applied to 2019-20 characteristics. Historical and Expansion G&T schools have a mean predicted probability of 0.27. Gained G&T schools have a mean predicted probability of 0.05, and 91% had predicted probabilities below 10% under the historical model. The Gained G&T distribution closely overlaps with the Never G&T distribution, not with the Historical and Expansion G&T distribution.

Table A6 compares school and local-area characteristics across Historical and Expansion, Gained, and Lost G&T schools. As in the original two-group comparison, Gained G&T schools differ sharply from the Historical and Expansion G&T group on nearly every dimension: they are located in lower-homeownership local contexts (24.4% vs. 44.6%) and they serve much poorer student populations (84.8% vs. 58.2% school poverty). Lost G&T schools are more intermediate. Relative to the Historical and Expansion G&T group, they remain somewhat less advantaged on tract homeownership (39.1% vs. 44.6%) and school poverty (73.8% vs. 58.2%), but they are still far closer to the historical G&T profile than the Gained group. This pattern suggests that the losses did not simply offset the differences observed in the gained sites.

V. Discussion

This study examined the geographic distribution of Gifted and Talented programs across New York City public schools from 2010 to 2024. We discuss three groups of findings.

Neighborhood-Level Inequality in G&T Access

First, G&T program presence is more strongly clustered by neighborhood than by district. In the pooled school-year empty model, the NTA ICC is 62.8% and the district ICC is 10.6%. In the 2019-20 cross-section, the absolute ICCs are smaller, but the same ordering remains: 7.2% for NTAs and 2.9% for districts. The difference in magnitude indicates that the exact variance shares are sensitive to the pooled panel structure and should not be treated as universal quantities. The consistent conclusion is that district boundaries conceal substantial within-district geographic differentiation in program presence. The within-district examples in Appendix Table A7 illustrate this pattern directly.

Among tract-level local-area characteristics, homeownership independently predicts G&T presence across all model specifications and in year-by-year robustness checks. This association is not reducible to tract poverty or education levels. It captures something additional about the communities in which G&T programs are located. Several mechanisms may explain this. Homeowners may have longer time horizons in their communities and stronger incentives to invest in local school quality, including participation in parent organizations and school governance (Chetty et al., 2022; Mordechay & Ayscue, 2024). Residential stability may also facilitate the sustained advocacy needed to establish and preserve specialized programs. Once G&T programs exist in stable neighborhoods, homeowning families may mobilize to protect them from policy changes, a dynamic consistent with the opportunity hoarding behaviors documented by Sattin-Bajaj and Roda (2020).

Community and School Characteristics Associated with G&T Placement

School-level racial composition does not predict G&T presence once neighborhood and district differences are accounted for. None of the four racial composition variables reach statistical significance in the multilevel models. This does not mean that race is unrelated to gifted education access more broadly. The descriptive data show large racial disparities, in that G&T schools have far higher White and Asian student shares and far lower Black and Hispanic shares than non-G&T schools. However, once neighborhood and district are held constant, a school's racial composition does not predict whether it hosts a G&T program. These results speak to program presence, not to disparities in identification, application, admission, or enrollment within neighborhoods. Expanding G&T programs into neighborhoods that currently lack them may therefore address one part of the broader access problem, but not the whole of it.

Among the tract-level covariates in M3, poverty is negatively associated with G&T presence (OR = 0.62, $p < .001$), reinforcing that program placement is tied to local economic conditions beyond what school-level poverty captures. Graduate degree attainment is not significant (OR = 1.11, $p = .26$), while homeownership remains significant in the same model. This pattern suggests that G&T program placement is more closely tied to residential stability and civic infrastructure than to nearby residents' formal education levels. Family-structure variables, which ranked highly in Stage 1, were not included in the multilevel models because they were highly collinear with homeownership ($r = 0.70$).

At the school level, the positive association between percent students with disabilities and G&T presence (OR = 1.21 to 1.23) likely reflects organizational capacity rather than a direct relationship between special education and gifted programming. The raw correlation between SWD share and G&T status is negative ($r = -0.14$) and the positive coefficient emerges only after controlling for enrollment, poverty, and other characteristics, indicating a suppression effect.

Schools with higher SWD rates for their size and poverty level tend to be comprehensive, full-service institutions that host multiple specialized programs.

The 2022-2024 Expansion

Third, the 2022-2024 G&T expansion represented a meaningful departure from the historical placement pattern. Schools that gained new G&T programs during the expansion had a mean predicted probability of only 0.05 under the historical model, compared to 0.27 for Historical and Expansion G&T schools. Ninety-one percent of expansion schools had predicted probabilities below 10%. The expansion schools were located in lower-homeownership, higher-poverty local contexts (25% vs. 45% homeownership and 23% vs. 13% poverty) and served student populations with combined Black and Hispanic shares of 79% compared to 44% for historical G&T schools. By placing programs in areas with substantially different demographic and socioeconomic profiles, the expansion departed sharply from the geographic patterns that had governed G&T placement for more than a decade. At the same time, the schools that lost G&T programs look more intermediate than the gained schools: in the appendix descriptives they remain much closer to the Historical and Expansion G&T profile than to the new Gained group on tract homeownership, tract income, and school poverty.

Nonetheless, the finding is important because it suggests that the expansion reached schools outside the historical placement profile. At the same time, the current analysis does not identify the mechanism behind either the historical concentration of programs or the new site-selection decisions. Questions about long-term sustainability and about who ultimately fills the new seats therefore remain open.

A related implication is that NYC’s expansion occurred without a corresponding citywide instructional foundation for what gifted education should look like across sites. Many of the city’s existing programs were created locally before NYC Public Schools centralized G&T admissions and eligibility, and they entered the current system with different histories, goals, and program models. As a result, the city expanded the geographic footprint of G&T more quickly than it established a coherent instructional vision across programs. For other large urban school systems considering similar expansion, the broader lesson may be to treat gifted education as a service to be designed and delivered coherently, rather than simply as a program location to be added.

Limitations

Our analysis examines where G&T programs are located, not who enrolls in them. Because NYC's district-level admissions process allows families to apply to programs outside their immediate neighborhood, the demographic composition of a G&T classroom may differ substantially from the school or neighborhood in which it is located. This disconnect underscores that physical availability is a necessary but not sufficient condition for equitable participation. Future research should examine whether supply-side expansions translate into enrollment gains for the communities in which new programs are placed, or whether existing patterns of information access and test preparation continue to shape who fills the seats.

Additionally, the foreign-born coefficient should be interpreted descriptively. We do not have tract-level subgroup measures that would allow us to identify which communities, if any, are driving that association. Future work with more detailed and complete ethnic subgroup data could investigate potential mechanisms more directly.

VI. Conclusion

This study demonstrates that the geography of G&T programs in New York City is patterned primarily at the neighborhood level. The majority of variation in G&T program presence occurs between neighborhoods within districts, not between districts themselves. Homeownership independently predicts program presence after accounting for school composition, district membership, and other tract-level local-area factors, while school-level racial composition does not predict G&T presence within neighborhoods. This finding suggests that researchers studying educational opportunity should look beyond district boundaries, which are administrative conveniences that can obscure the community-level factors shaping which schools receive advanced programming.

The city's 2022-2024 expansion reached schools and neighborhoods with fundamentally different profiles than those that historically hosted G&T programs. Because substantial variation in G&T program presence exists at the neighborhood level, policies aimed at equity in gifted education must address not only how students are identified but also where programs are located. The expansion provides descriptive evidence that deliberate policy action can depart from entrenched geographic patterns of educational opportunity. Whether it represents a lasting structural change or a temporary policy departure remains to be seen.

References

Bates, D. M. (2010). lme4: Mixed-effects modeling with R.

Bergman, P., Chetty, R., DeLuca, S., Hendren, N., Katz, L. F., & Palmer, C. (2024). Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice. *The American Economic Review, 114*(5), 1281-1337. https://doi.org/10.1257/aer.20200407

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and regression trees.* Wadsworth.

Carman, C. A., Walther, C. A. P., & Bartsch, R. A. (2018). Using the cognitive abilities test (CogAT) 7 nonverbal battery to identify the Gifted/Talented: An investigation of demographic effects and norming plans. *The Gifted Child Quarterly, 62*(2), 193-209. https://doi.org/10.1177/0016986217752097

Card, D., & Giuliano, L. (2016a). Can tracking raise the test scores of high-ability minority students? American Economic Review, 106(10), 2783-2816.

Card, D., & Giuliano, L. (2016b). Universal screening increases the representation of low-income and minority students in gifted education. Proceedings of the National Academy of Sciences, 113(48), 13678-13683.

Chetty, R. & Hendren, N. (2018). the impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The Quarterly Journal of Economics, 133*(3), 1107-1162. https://doi.org/10.1093/qje/qjy007

Chetty, R., Hendren, N., Jones, M. R., & Porter, S. R. (2020). Race and economic opportunity in the United States: An intergenerational perspective. *The Quarterly Journal of Economics, 135*(2), 711-783. https://doi.org/10.1093/qje/qjz042

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., Johnston, D., Koenen, M., Laguna-Muggenburg, E., Mudekereza, F., Rutter, T., Thor, N., Townsend, W., Zhang, R., Bailey, M., . . . Wernerfelt, N. (2022). Social capital I: Measurement and associations with economic mobility. *Nature (London), 608*(7921), 108-121. https://doi.org/10.1038/s41586-022-04996-4

Corcoran, S. P., & Baker-Smith, E. C. (2018). Pathways to an elite education: Application, admission, and matriculation to New York City's specialized high schools. *Education Finance and Policy*, *13*(2), 256-279.

Dixson, D. D., Peters, S. J., Plucker, J. A., & Callahan, C. M. (2025). The (conference) room where it happens: Explaining disproportional representation in gifted and talented education. *AERA Open, 11*. https://doi.org/10.1177/23328584251369849

Ford, D. Y., Wright, B. L., & Trotman Scott, M. (2020). A matter of equity: Desegregating and integrating gifted and talented education for under-represented students of color. *Multicultural Perspectives (Mahwah, N.J.), 22*(1), 28-36. https://doi.org/10.1080/15210960.2020.1728275

Green, T. L., Sánchez, J., & Germain, E. (2017). Communities and school ratings: Examining geography of opportunity in an urban school district located in a resource-rich city. *The Urban Review, 49*(5), 777-804. https://doi.org/10.1007/s11256-017-0421-1

Grissom, J. A., Redding, C., & Bleiberg, J. F. (2019). Money over merit? Socioeconomic gaps in receipt of gifted services. Harvard Educational Review, 89(3), 337-369. https://doi.org/10.17763/1943-5045-89.3.337

Hines, E. M., Fletcher, E. C., Ford, D. Y., Moore, J. L., & Middleton, T. J. (2022). A tale of two pandemics: Interrogating discrimination against black students in gifted education and other programs for advanced learners. *The Journal of Negro Education, 91*(3), 408-415.

Kafka, J., & Matheny, C. (2021). Boundary matters: Uncovering the hidden history of New York City's school subdistrict lines. AERA Open, 7. https://doi.org/10.1177/23328584211038939

Lu, Y., Weinberg, S. L., & McCormick, M. (2020). Test-taking for gifted and talented kindergarten: Underscoring the importance of outreach. *The Gifted Child Quarterly, 64*(4), 259-274. https://doi.org/10.1177/0016986220941587

Mordechay, K., & Ayscue, J. B. (2024). Diversifying neighborhoods, diversifying schools? the relationship between neighborhood racial change and school segregation in New York City. *Education and Urban Society, 56*(1), 3-32. https://doi.org/10.1177/00131245221110555

More, A. S., & Rana, D. P. (2017, October). Review of random forest classification techniques to resolve data imbalance. In *2017 1st International conference on intelligent systems and information management (ICISIM)* (pp. 72-78). IEEE.

Peters, S. J. (2022). The challenges of achieving equity within public school gifted and talented programs. *The Gifted Child Quarterly, 66*(2), 82-94. https://doi.org/10.1177/00169862211002535

Peters, S. J., & Carter, J. S. (2022). Predictors of access to gifted education: What makes for a successful school? *Exceptional Children, 88*(4), 341-358. https://doi.org/10.1177/00144029221081092

Peters, S. J., & Gentry, M. (2010). Multigroup construct validity evidence of the HOPE scale: Instrumentation to identify low-income elementary students for gifted programs. Gifted Child Quarterly, 54(4), 298-313. https://doi.org/10.1177/0016986210378332

Peters, S. J., Gentry, M., Whiting, G. W., & McBee, M. T. (2019). Who gets served in gifted education? Demographic representation and a call for action. *Gifted Child Quarterly*, *63*(4), 273-287.

Plucker, J. A., Wells, A., & Meyer, M. S. (2022). Identification policy: Addressing equity and excellence for advanced learners. *Gifted Child Today Magazine, 45*(4), 201-211. https://doi.org/10.1177/10762175221110942

Plucker, J. A., Burroughs, N., & Song, R. (2010). Mind the (Other) Gap! The Growing Excellence Gap in K-12 Education. *Center for Evaluation and Education Policy, Indiana University*.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Sage.

Sattin-Bajaj, C., & Roda, A. (2020). Opportunity hoarding in school choice contexts: The role of policy design in promoting middle-class parents' exclusionary behaviors. *Educational Policy (Los Altos, Calif.)*, 34(7), 992-1035. https://doi.org/10.1177/0895904818802106

Snijders, T. A. B., & Bosker, R. J. (2012). Multilevel analysis: An introduction to basic and advanced multilevel modeling (2nd ed.). Sage.

Tate, W. F. (2008). "Geography of Opportunity": Poverty, place, and educational outcomes. *Educational Researcher, 37*(7), 397-411. https://doi.org/10.3102/0013189X08326409

Tran, B. T. N., Wai, J., McKenzie, S., Mills, J., & Seaton, D. (2022). Expanding gifted identification to capture academically advanced, low-income, or other disadvantaged students: The case of Arkansas. Journal for the Education of the Gifted, 45(1), 64-83. https://doi.org/10.1177/01623532211063936

Turk, U., & Osth, J. (2019). How much does geography contribute? measuring inequality of opportunities using a bespoke neighbourhood approach. *Journal of Geographical Systems, 21*(2), 295-318. https://doi.org/10.1007/s10109-019-00297-z

Yaluma, C. B., & Tyner, A. (2021). Are U.S. schools closing the "Gifted gap"? analyzing elementary and middle schools' gifted participation and representation trends (2012-2016). *Journal of Advanced Academics, 32*(1), 28-53. https://doi.org/10.1177/1932202X20937633

Yeung, G., & Mun, R. U. (2022). A renewed call for disaggregation of racial and ethnic data: Advancing scientific rigor and equity in gifted and talented education research. *Journal for the Education of the Gifted, 45*(4), 319-351. https://doi.org/10.1177/01623532221123795

Tables and Figures

Table 1.

Schools with G&T Programs by Year and Borough, 2010-2024

Year	**Bronx**	**Brooklyn**	**Manhattan**	**Queens**	**Staten Island**	**Citywide**
2010-11	9 (2.3%)	49 (9.3%)	19 (5.7%)	32 (9.1%)	6 (7.9%)	115 (6.8%)
2011-12	9 (2.3%)	49 (9.4%)	20 (6%)	31 (8.8%)	5 (6.6%)	114 (6.8%)
2012-13	7 (1.7%)	50 (9.5%)	20 (6%)	30 (8.5%)	6 (7.8%)	113 (6.6%)
2013-14	7 (1.7%)	39 (7.2%)	21 (6.2%)	30 (8.2%)	8 (10.1%)	105 (6%)
2014-15	7 (1.7%)	35 (6.5%)	20 (5.8%)	31 (8.3%)	9 (11.1%)	102 (5.8%)
2015-16	6 (1.4%)	34 (6.3%)	20 (5.9%)	31 (8.1%)	9 (11%)	100 (5.7%)
2016-17	9 (2.2%)	34 (6.5%)	19 (5.7%)	31 (8.1%)	9 (10.8%)	102 (5.9%)
2017-18	9 (2.2%)	33 (6.3%)	20 (6%)	31 (8.1%)	9 (10.8%)	102 (5.9%)
2018-19	10 (2.5%)	31 (6%)	20 (6.2%)	31 (8.1%)	8 (9.6%)	100 (5.8%)
2019-20	10 (2.6%)	30 (5.8%)	20 (6.2%)	29 (7.6%)	7 (8.5%)	96 (5.7%)
2020-21	9 (2.3%)	27 (5.2%)	19 (5.9%)	26 (6.8%)	7 (8.5%)	**88 (5.2%)**
2021-22	9 (2.3%)	29 (5.6%)	19 (5.9%)	26 (6.8%)	6 (7.4%)	**89 (5.3%)**
2022-23	13 (3.4%)	43 (8.3%)	22 (6.8%)	39 (10.1%)	7 (8.3%)	124 (7.3%)
2023-24	15 (3.9%)	41 (7.9%)	23 (7.1%)	35 (9.1%)	6 (7.2%)	120 (7.1%)

Note. Schools are classified as having a G&T program if they enrolled 10 or more G&T-identified students. 2023-24 uses admissions data rather than student-level G&T identification due to the introduction of universal screening. Districts 75 and 79 are excluded.

Table 2.

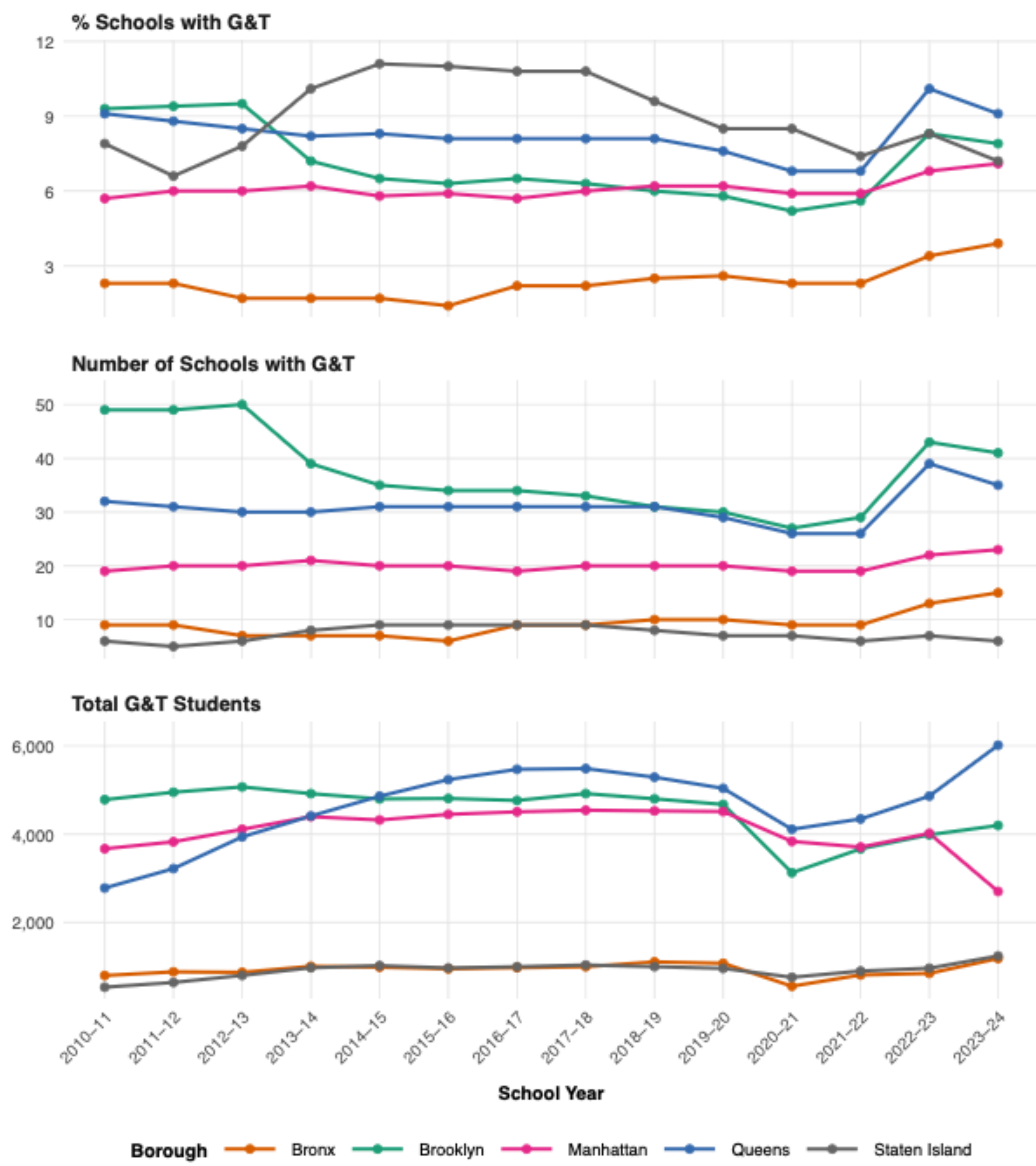
G&T vs Non-G&T School Characteristics by Borough, 2019-20

Metric	Group	Bronx	SMD	Brooklyn	SMD	Manhattan	SMD	Queens	SMD	Staten Island	SMD	Citywide	SMD
N (schools)	G&T Schools	10		30		20		29		7		96	
	Non-G&T Schools	378		484		304		353		75		1595	
Mean G&T Students	G&T Schools	108	—	156	—	226	—	174	—	137	—	169	—
% School in G&T	G&T Schools	15.8	—	21.8	—	37.4	—	21	—	17.4	—	23.8	—
Enrollment	G&T Schools	748.4	0.51	796.9	0.35	610.9	0.36	882.7	0.11	828	-0.03	781.3	0.03
	Non-G&T Schools	549.9		590.3		479.7		810		850.5		688.6	
% Black	G&T Schools	28.9	0.19	25	-0.54	17.6	-0.28	8.8	-0.52	3.8	-0.85	17.4	-0.46
	Non-G&T Schools	26.2		41.5		22.4		22.1		15.4		28.7	
% Hispanic	G&T Schools	60.2	-0.24	25.9	-0.23	38.2	-0.41	32.8	-0.18	22.7	-0.62	33.8	-0.39
	Non-G&T Schools	64		31		48.5		37		32.2		43.5	
% White	G&T Schools	6	0.34	28.5	0.82	19	0.15	20.2	0.57	58.8	0.83	23.9	0.64
	Non-G&T Schools	3.8		13.7		16.1		11.9		38.8		12.6	
% Asian	G&T Schools	3.5	-0.08	18.6	0.49	21.6	0.8	34.3	0.46	12.3	0.22	21.9	0.59
	Non-G&T Schools	4		10.8		9.4		24.9		10.4		12	
% Poverty	G&T Schools	81.1	-0.69	69.3	-0.51	60.7	-0.35	62.6	-0.58	49.7	-0.65	65.3	-0.59
	Non-G&T Schools	88.2		78.6		69.9		72.1		63.6		77.1	
% ELL	G&T Schools	12.3	-0.4	14.7	0.14	10.9	-0.07	14.9	0.02	5.4	-0.37	13.1	-0.08
	Non-G&T Schools	18.6		12.8		11.9		14.6		8		14.2	
% SWD	G&T Schools	20.8	-0.31	20.8	-0.23	23.9	-0.07	16.6	-0.23	24.9	-0.34	20.5	-0.23
	Non-G&T Schools	25.9		24.6		25.1		20.4		31.4		24.4	
Tract: % Grad Degree	G&T Schools	10.5	1.27	15.8	0.35	28.7	0.3	13.2	0.34	13.6	0.43	17	0.39
	Non-G&T Schools	5.3		12.7		24.7		11.3		12.4		12.9	
Tract: % Owner-Occupied	G&T Schools	29.1	0.96	34.4	0.66	24.2	0.44	48.6	0.2	76.3	0.77	39.1	0.55
	Non-G&T Schools	15.5		26.3		18.9		44.7		65.1		28.1	
Tract: % Poverty	G&T Schools	25.1	-0.79	20	-0.41	18.4	-0.13	12.9	-0.29	8.3	-0.85	17.2	-0.5
	Non-G&T Schools	33.8		23.8		19.8		14.6		14.7		23	
Tract: % Single Mom w/ Kids	G&T Schools	15	-0.75	7.2	-0.53	5.4	-0.14	5	-0.48	4.7	-0.74	6.8	-0.56
	Non-G&T Schools	18.9		10.1		6.1		6.8		7.7		10.6	
Tract: % Foreign Born	G&T Schools	31.1	-0.45	36	0.07	28.1	-0.23	46.2	0.04	17.7	-0.88	35.6	-0.02
	Non-G&T Schools	34.5		35.2		30.5		45.7		23		35.8	
Tract: Median HH Income	G&T Schools	46687	0.99	58702	0.29	79651	0.21	64725	0.27	84582	0.89	65521	0.43
	Non-G&T Schools	33340		52269		71673		61115		71285		54284	

Note. Means for schools with and without G&T programs in 2019-20, shown separately by borough. SMD = standardized mean difference (positive values indicate G&T schools are higher). Schools classified as G&T if they enrolled 10 or more G&T-identified students.

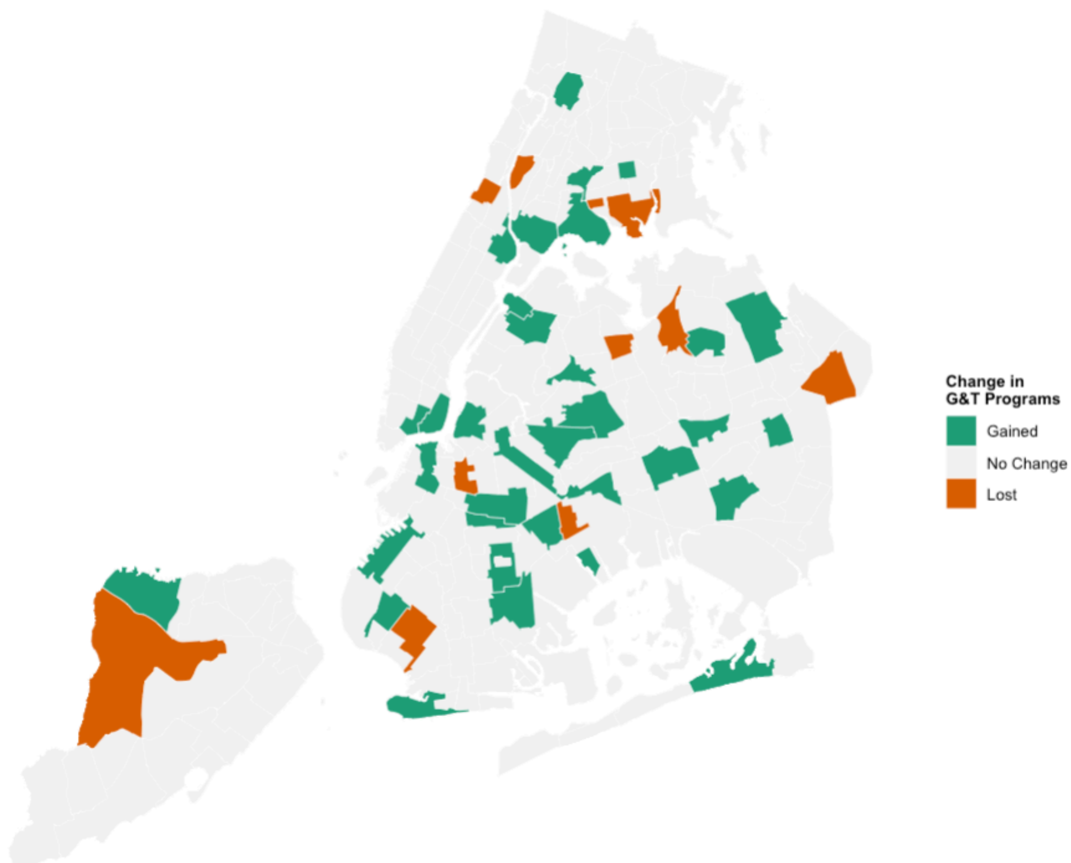
Figure 1.

Trends in G&T Program Distribution across NYC Boroughs, 2010-2024



Note. Panel A shows the percentage of schools with G&T programs. Panel B shows the number of schools with G&T programs. Panel C shows total G&T students.

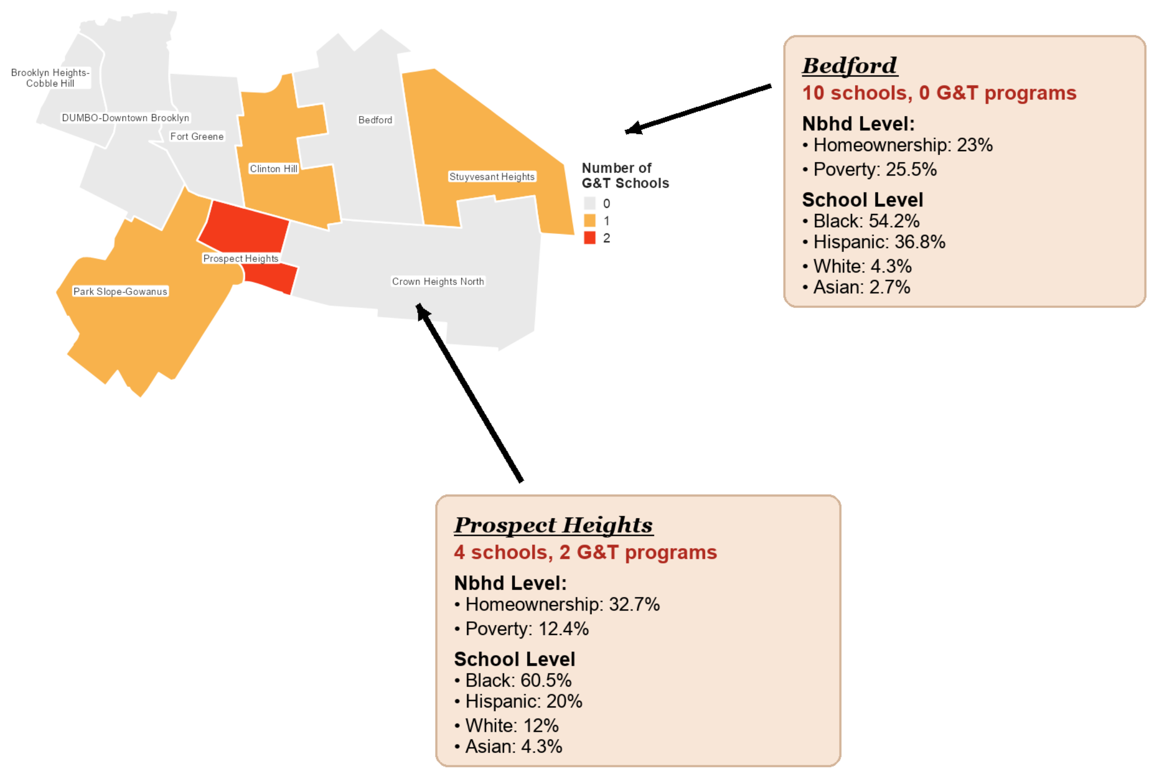
Figure 2.
Change in G&T Programs by Neighborhood: 2019-20 to 2022-23



Note. Neighborhoods defined by Neighborhood Tabulation Areas (NTAs). "Gained" neighborhoods contain at least one school that added a G&T program between 2019-20 and 2022-23. "Lost" neighborhoods contain at least one school that dropped a G&T program; "No Change" neighborhoods retained the same G&T status. Neighborhoods with no G&T activity in either year are shown in light gray. Schools are classified as having a G&T program if they enrolled 10 or more G&T-identified students.

Figure 3.

Illustrative Within-District Contrast in District 13 (Brooklyn), 2019-20



Note. Callout boxes highlight two neighborhoods within District 13 that differed sharply in local G&T access before the expansion. Bedford had 10 schools and no G&T programs in 2019-20, while Prospect Heights had G&T programs in 2 of 4 schools. The figure pairs G&T access with tract-based homeownership and poverty indicators, along with average school racial composition, to illustrate the kind of within-district variation that district-level summaries can obscure.

Table 3.
Variance Decomposition across Districts and NTAs in Pooled School-Year Models

Model	σ^2 District	σ^2 NTA	Residual variance	ICC District	ICC NTA	Residual share	AIC
M0: Empty	1.305	7.768	3.29	0.106	0.628	0.266	5985
M1: + School demographics	1.192	7.563	3.29	0.099	0.628	0.273	5832.4
M2: + School + Homeownership	1.164	7.197	3.29	0.1	0.618	0.282	5815.4
M3: + School + Curated Tract Controls	1.35	8.153	3.29	0.106	0.637	0.257	5740.3

Note. Cross-classified multilevel logistic regression with random intercepts for Neighborhood Tabulation Area (NTA) and school district. ICC = intraclass correlation coefficient, representing the proportion of total variance attributable to each level. Residual variance refers to the fixed logistic residual; residual share reports its proportion of total variance and should not be interpreted as a school-level random effect. M0 = empty model (random intercepts only); M1 = school demographics; M2 = M1 + tract-level percent owner-occupied housing; M3 = M2 + tract-level percent with graduate degree, percent in poverty, and percent foreign-born. All predictors standardized prior to estimation. Historical period: 2010-11 through 2019-20

Table 4.

Multilevel Logistic Regression: Predictors of G&T Program Presence, 2010-2020

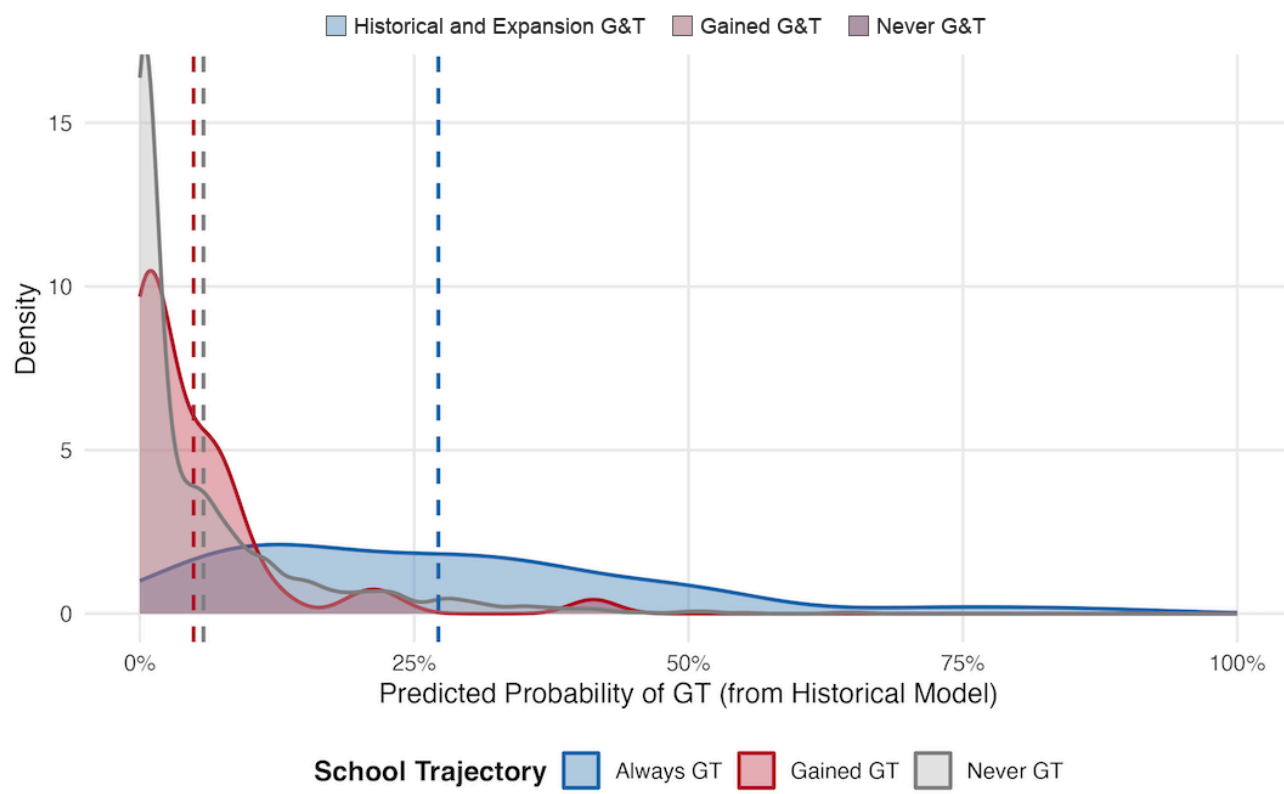
Model	Variable	Estimate	SE	z_value	p_value	OR
M1: School only	(Intercept)	-4.4883	0.3545	-12.66	< .001	0.011
	Total Students	0.1608	0.036	4.47	< .001	1.174
	Percent Poverty	-0.0662	0.0638	-1.04	0.2992	0.936
	Percent Black	-0.5183	0.4645	-1.12	0.2645	0.596
	Percent Hispanic	-0.1328	0.4343	-0.31	0.7599	0.876
	Percent Asian	0.4335	0.3036	1.43	0.1534	1.543
	Percent White	0.0884	0.3383	0.26	0.7937	1.092
	Percent ELL	-0.1129	0.0643	-1.76	0.0792	0.893
	Percent SWD	0.2061	0.0489	4.22	< .001	1.229
M3: + Curated Tract Controls	(Intercept)	-4.7464	0.3746	-12.67	< .001	0.009
	Total Students	0.1303	0.0367	3.55	0.0004	1.139
	Percent Poverty (School)	-0.0906	0.0647	-1.4	0.1616	0.913
	Percent Black	-0.3537	0.4684	-0.76	0.4501	0.702
	Percent Hispanic	-0.0319	0.438	-0.07	0.9419	0.969
	Percent Asian	0.4618	0.306	1.51	0.1313	1.587
	Percent White	0.13	0.3408	0.38	0.7028	1.139
	Percent ELL	-0.1263	0.0666	-1.9	0.0578	0.881
	Percent SWD	0.1896	0.0493	3.84	0.0001	1.209
	Percent Owner Occupied	0.225	0.0801	2.81	0.005	1.252
	Percent Grad Degree	0.1016	0.0893	1.14	0.255	1.107
	Percent Poverty (Tract)	-0.4836	0.094	-5.15	< .001	0.617
	Percent Foreign Born	0.5259	0.0814	6.46	< .001	1.692

Note. Odds ratios from cross-classified multilevel logistic regression with random intercepts for NTA and district. School-level demographics computed excluding G&T-identified students (general education population) to prevent mechanical contamination. All predictors standardized; odds ratios reflect a one standard deviation change. M1 includes school demographics only. M2 (removed for space) adds tract-level percent owner-occupied housing. M3 adds tract-level percent with graduate degree, percent in poverty, and percent foreign-born. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Appendix

Figure A1.

Predicted Probability of G&T Program Presence under the Historical Model, by School Trajectory



Note. Predicted probabilities generated from Model 1 (school demographics with NTA and district random intercepts) applied to 2019-20 school characteristics. "Historical and Expansion G&T" schools had G&T programs during both the historical (2010-20) and expansion (2022-24) periods. "Gained G&T" schools received new G&T programs during 2022-24. "Never G&T" schools never had G&T programs in any year. Dashed vertical lines indicate group means. 91% of Gained G&T schools had predicted probabilities below 10%.

Table A1.
Random Forest Variable Importance Rankings

Rank	Variable	Type	Mean Decrease Accuracy	Mean Decrease Gini
1	Enrollment	School	121.82	301.81
2	% ELL	School	63.54	70.99
3	% Hispanic	School	52.7	71.45
4	Tract: % Income $200K+	Tract	47.82	64.95
5	Tract: % Less Than High School	Tract	47.75	66.19
6	% Students with Disabilities	School	47.31	56.38
7	Tract: % Receiving SNAP	Tract	46.29	104.4
8	% White	School	46.12	66.61
9	Tract: Median Rent	Tract	44.46	64.62
10	Tract: % Married w/ Children	Tract	44.45	49.45
11	Tract: % Foreign Born	Tract	43.37	89.38
12	Tract: % Same House 1 Year	Tract	43.33	64.47
13	Tract: % Crowded Housing	Tract	43.18	46.12
14	Tract: % Large Building (20+ Units)	Tract	43.04	50.25
15	Tract: % Bachelor's Degree+	Tract	42.79	44.3
16	Tract: % Owner-Occupied	Tract	42.61	74.02
17	Tract: % Single Mother w/ Children	Tract	42.43	57.18
18	Tract: % Professional Occupation	Tract	42.11	63.67
19	Tract: % Graduate Degree	Tract	42.07	44.55
20	% Asian	School	41.6	60.93
21	Tract: % Unemployed	Tract	41.5	78.57
22	Tract: % Married-Couple Family	Tract	41.16	61.25
23	Tract: % Rent Burdened (50%+)	Tract	40.93	53.83
24	Tract: % Not Citizen	Tract	39.76	47.19

25	Tract: % Naturalized Citizen	Tract	39.19	70.16
26	Tract: % Service Occupation	Tract	38.94	62.7
27	% Black	School	38.69	79.98
28	Tract: % Poverty	Tract	38.63	54.94
29	Tract: Per Capita Income	Tract	38.23	51.2
30	% Poverty (School)	School	37.32	52.43
31	Tract: % Rent Burdened (35%+)	Tract	37.1	63.34
32	Tract: % Public Transit Commute	Tract	36.58	48.36
33	Tract: % Single-Family Home	Tract	34.53	39.3
34	Tract: Median Household Income	Tract	32.67	92.75
35	Tract: % Work from Home	Tract	32.3	48.54

Note. Variable importance from a Random Forest classifier with 500 trees, fit on pooled 2010-20 school-year data. Mean Decrease in Accuracy measures the drop in out-of-bag prediction accuracy when each variable is randomly permuted. G&T class upweighted by factor of 10 to address class imbalance. 8 school-level and 27 tract-level ACS predictors included.

Table A2.
High Correlation Pairs

Var1	Var2	r
Tract: % Bachelor's Degree+	Tract: % Graduate Degree	0.949
Tract: % Professional Occupation	Tract: % Bachelor's Degree+	0.94
Tract: Per Capita Income	Tract: % Income $200K+	0.93
Tract: % Professional Occupation	Tract: % Graduate Degree	0.912
Tract: Per Capita Income	Tract: % Bachelor's Degree+	0.89
Tract: Per Capita Income	Tract: % Graduate Degree	0.889
Tract: Median Household Income	Tract: % Income $200K+	0.868
Tract: % Professional Occupation	Tract: % Service Occupation	-0.868
Tract: % Poverty	Tract: % Receiving SNAP	0.863
Tract: % Rent Burdened (35%+)	Tract: % Rent Burdened (50%+)	0.862
Tract: % Income $200K+	Tract: % Graduate Degree	0.859
Tract: Median Household Income	Tract: Per Capita Income	0.847
Tract: % Income $200K+	Tract: % Bachelor's Degree+	0.847
Tract: Per Capita Income	Tract: % Professional Occupation	0.842
Tract: Median Household Income	Tract: Median Rent	0.841
Tract: % Service Occupation	Tract: % Bachelor's Degree+	-0.826
Tract: Median Household Income	Tract: % Bachelor's Degree+	0.813
Tract: % Income $200K+	Tract: % Professional Occupation	0.811
Tract: Median Household Income	Tract: % Graduate Degree	0.802
Tract: % Receiving SNAP	Tract: % Less Than High School	0.802
Tract: % Foreign Born	Tract: % Naturalized Citizen	0.797
Tract: % Service Occupation	Tract: % Graduate Degree	-0.79
Tract: Median Household Income	Tract: % Professional Occupation	0.783
Tract: Median Household Income	Tract: % Receiving SNAP	-0.779
Tract: Median Household Income	Tract: % Service Occupation	-0.761
Tract: % Foreign Born	Tract: % Not Citizen	0.76
Tract: % Income $200K+	Tract: Median Rent	0.759

Tract: % Receiving SNAP	Tract: % Single Mother w/ Children	0.758
Tract: % Professional Occupation	Tract: % Less Than High School	-0.756
Tract: % Less Than High School	Tract: % Bachelor's Degree+	-0.756
Tract: Median Rent	Tract: % Bachelor's Degree+	0.754
Tract: % Poverty	Tract: % Less Than High School	0.746
Tract: Median Household Income	Tract: % Poverty	-0.745
Tract: % Receiving SNAP	Tract: % Service Occupation	0.743
Tract: Per Capita Income	Tract: % Service Occupation	-0.742
Tract: Per Capita Income	Tract: Median Rent	0.742
Tract: Median Household Income	Tract: % Less Than High School	-0.737
Tract: % Service Occupation	Tract: % Less Than High School	0.731
Tract: % Owner-Occupied	Tract: % Single-Family Home	0.727
Tract: % Income $200K+	Tract: % Service Occupation	-0.721
Tract: % Less Than High School	Tract: % Graduate Degree	-0.718
Tract: Median Rent	Tract: % Graduate Degree	0.717
Tract: % Poverty	Tract: % Single Mother w/ Children	0.705
Tract: % Married-Couple Family	Tract: % Married w/ Children	0.703
Tract: % Receiving SNAP	Tract: % Bachelor's Degree+	-0.702
Tract: % Owner-Occupied	Tract: % Married-Couple Family	0.702

Table A3.
Likelihood Ratio Tests and Model Fit Comparisons

Comparison	AIC simple	AIC complex	Delta AIC
M0 vs M1	5985	5832.4	-152.6
M1 vs M2	5832.4	5815.4	-17
M2 vs M3	5815.4	5740.3	-75.1

Note. Likelihood ratio tests comparing nested multilevel models. AIC = Akaike Information Criterion (lower is better). All models are cross-classified multilevel logistic regressions with random intercepts for NTA and district. M0 = empty model (random intercepts only). M1 adds school demographics (enrollment, percent poverty, race/ethnicity, ELL, students with disabilities). M2 adds tract-level homeownership. M3 adds tract-level graduate degree attainment, poverty, and percent foreign born. Historical period: 2010-11 through 2019-20. All predictors standardized prior to estimation.

Table A4.
School Trajectory Group Counts

Trajectory	N	Percent
Historical and Expansion G&T	87	4.8
Gained G&T	43	2.4
Lost G&T	62	3.4
Never G&T	1612	89.4

Note. Schools classified based on G&T program status across the historical period (2010-20) and expansion period (2022-24). "Historical and Expansion G&T" = G&T in both periods; "Gained G&T" = no G&T historically, G&T during expansion; "Lost G&T" = G&T historically, none during expansion; "Never G&T" = no G&T in any year. COVID years (2020-22) excluded from classification.

Table A5.
Cross-Method Variable Importance: Random Forest vs CART

Variable	Type	RF_Rank	RF_MDA	CART_Rank	CART_Pct
Enrollment	School	1	121.82	1	20.2
% ELL	School	2	63.54	21	1.2
% Hispanic	School	3	52.7	13	2.4
Tract: % Income $200K+	Tract	4	47.82	4	6.1
Tract: % Less Than High School	Tract	5	47.75	19	1.5
% Students with Disabilities	School	6	47.31	30	0.5
Tract: % Receiving SNAP	Tract	7	46.29	15	1.7
% White	School	8	46.12	3	7.5
Tract: Median Rent	Tract	9	44.46	23	1
Tract: % Married w/ Children	Tract	10	44.45	18	1.5
Tract: % Foreign Born	Tract	11	43.37	24	0.9
Tract: % Same House 1 Year	Tract	12	43.33	28	0.5
Tract: % Crowded Housing	Tract	13	43.18	27	0.5
Tract: % Large Building (20+ Units)	Tract	14	43.04	31	0.4
Tract: % Bachelor's Degree+	Tract	15	42.79	12	3.5
Tract: % Owner-Occupied	Tract	16	42.61	16	1.7
Tract: % Single Mother w/ Children	Tract	17	42.43	32	0.4
Tract: % Professional Occupation	Tract	18	42.11	7	4.5
Tract: % Graduate Degree	Tract	19	42.07	22	1.1
% Asian	School	20	41.6	6	5.5
Tract: % Unemployed	Tract	21	41.5	35	0
Tract: % Married-Couple Family	Tract	22	41.16	5	6
Tract: % Rent Burdened (50%+)	Tract	23	40.93	25	0.8
Tract: % Not Citizen	Tract	24	39.76	29	0.5
Tract: % Naturalized Citizen	Tract	25	39.19	34	0.3
Tract: % Service Occupation	Tract	26	38.94	11	3.6
% Black	School	27	38.69	2	7.8

Tract: % Poverty	Tract	28	38.63	20	1.4
Tract: Per Capita Income	Tract	29	38.23	8	4.3
% Poverty (School)	School	30	37.32	14	2.4
Tract: % Rent Burdened (35%+)	Tract	31	37.1	33	0.3
Tract: % Public Transit Commute	Tract	32	36.58	17	1.6
Tract: % Single-Family Home	Tract	33	34.53	9	4.1
Tract: Median Household Income	Tract	34	32.67	10	4
Tract: % Work from Home	Tract	35	32.3	26	0.6

Note. Variable importance rankings from Random Forest (Mean Decrease in Accuracy) and CART (reduction in splitting criterion). Both models fit on pooled 2010-20 data with 35 predictors and no district controls.

Table A6.
Historical and Expansion, Gained, and Lost G&T School Mean Differences, 2019-20

Variable	Historical and Expansion G&T (mean)	Gained G&T (mean)	Lost G&T (mean)	SMD (Gained vs Historical and Expansion)	SMD (Lost vs Historical and Expansion)
Enrollment	787.5	581.6	718.7	-0.69	-0.22
% Poverty	58.2	84.8	73.8	1.53	0.74
% Black	15.6	35.5	27.8	0.78	0.50
% Hispanic	28.6	44.0	33.1	0.65	0.20
% Asian	25.6	12.8	18.1	-0.60	-0.36
% White	26.3	5.8	17.8	-1.28	-0.41
% ELL	10.5	15.3	14.2	0.51	0.41
% SWD	16.5	22.8	19.5	0.98	0.56
Tract: % Owner-Occupied	44.6	24.4	39.1	-0.86	-0.22
Tract: % Grad Degree	19.5	8.4	13.4	-1.13	-0.53
Tract: % Poverty	13.2	22.8	17.2	0.87	0.38
Tract: Median HH Income	80186.5	51518.6	67558.2	-1.07	-0.43
Tract: % Foreign Born	35.4	37.4	35.6	0.14	0.02

Note. Means for schools in the Historical and Expansion, Gained, and Lost G&T groups, measured on 2019-20 school and tract-level local-area characteristics. SMD columns compare the Gained and Lost groups to the Historical and Expansion group.

Table A7.
Within-District Neighborhood Variation in G&T Access, 2019-20

District	Neighborhood	N Schools	N G&T	% G&T	% Owner-Occupied	% Student Poverty	% Grad Degree	Median HH Income
District 2								
	Upper East Side-Carnegie Hill	3	2	66.7	57.5	18.7	53.1	171312
	Gramercy	14	0	0	41.4	61.6	41.4	127218
	West Village	5	0	0	38	49.1	44.5	145847
	Turtle Bay-East Midtown	3	0	0	36.3	29.2	44	161944
	SoHo-TriBeCa-Civic Center-Little Italy	5	1	20	34.5	40.7	34	163631
	Hudson Yards-Chelsea-Flatiron-Union Square	20	2	10	33.1	57.6	35.6	122672
	Lenox Hill-Roosevelt Island	12	1	8.3	29	35.8	35.5	123425
	Yorkville	5	0	0	25.7	33.9	42.2	113630
	Murray Hill-Kips Bay	4	0	0	23.6	77.6	35.2	119667
	Battery Park City-Lower Manhattan	12	0	0	21.9	48.8	41.5	192965
	Clinton	14	1	7.1	16.5	70.8	29.5	87363
	Midtown-Midtown South	3	0	0	12.7	77.1	21.7	62800
	Chinatown	16	1	6.2	9.4	77.8	10	42567
	Lower East Side	1	0	0	4.1	96.3	4.9	16600
District 13								
	Brooklyn Heights-Cobble Hill	1	0	0	50.9	10.6	42.2	96250
	Prospect Heights	1	1	100	32.3	39.2	36	123274
	Park Slope-Gowanus	3	1	33.3	31.8	50.9	35.5	131668
	DUMBO-Vinegar Hill-Downtown Brooklyn-Boerum Hill	10	0	0	31.4	80.2	33.5	124069
	Clinton Hill	8	1	12.5	31	77	21.3	81761

	Bedford	6	0	0	25.9	90.4	17.8	64678
	Fort Greene	8	0	0	22.3	73.7	26.3	97796
	Stuyvesant Heights	1	0	0	22.1	95.5	10.9	50290
	Crown Heights North	2	0	0	6.4	90.4	17.3	66252
District 20								
	Dyker Heights	5	0	0	55.9	75.3	11.7	81756
	Bath Beach	4	2	50	47.1	76.1	9.5	70362
	Bensonhurst West	7	2	28.6	45.1	74.6	8.6	56271
	Bensonhurst East	2	1	50	41.2	38	21.2	60708
	Bay Ridge	8	2	25	41	69.1	19.7	86188
	Kensington-Ocean Parkway	2	0	0	40.5	85.4	23.2	56726
	Borough Park	9	1	11.1	39	86.4	6.7	50386
	Sunset Park West	3	0	0	22.8	93.2	8.1	36147
	Sunset Park East	3	0	0	22.8	91.9	4.2	50050

Note. Districts 2 (Manhattan), 13 (Brooklyn), and 20 (Brooklyn) selected to illustrate within-district variation in local homeownership and G&T program access. Each row represents a Neighborhood Tabulation Area (NTA). % G&T = percentage of schools in the NTA with a G&T program. % Owner-Occupied and other local-area characteristics summarize tract-level ACS values for schools in the NTA. % Student Poverty is the mean across schools within the NTA. Within-district correlations between homeownership and % G&T are r = 0.62 (District 2), r = 0.18 (District 13), and r = 0.36 (District 20).

Table A8.
Year-by-Year Homeownership Coefficients from Cross-Classified Multilevel Models, 2010-2020

Year	N Schools	N G&T	Homeownership Coef.	Homeownership SE	Homeownership OR	Homeownership P value	AIC
2010-11	1368	114	0.184	0.123	1.203	0.1332	742.4
2011-12	1395	113	0.169	0.124	1.184	0.1744	748.4
2012-13	1428	112	0.3	0.127	1.35	0.0183	727.7
2013-14	1479	104	0.262	0.13	1.3	0.0437	697.7
2014-15	1503	101	0.267	0.128	1.306	0.0372	681.1
2015-16	1512	99	0.29	0.13	1.336	0.0261	671.4
2016-17	1514	101	0.313	0.116	1.367	0.0069	696.6
2017-18	1522	101	0.318	0.116	1.374	0.006	697.6
2018-19	1498	99	0.333	0.126	1.395	0.008	689.3
2019-20	1497	95	0.3	0.117	1.349	0.0105	671
Pooled (2010-20)	14716	1039	0.2716	0.0624	1.312	0	5815.4

Note. Homeownership coefficient from M2 (school demographics + tract-level homeownership) estimated separately for each year, 2010-11 through 2019-20. All models are cross-classified multilevel logistic regressions with random intercepts for NTA and district. OR = odds ratio. Pooled estimate included for comparison. Single-year models show singular fit warnings due to limited within-NTA variation in individual cross-sections; coefficient estimates remain interpretable. All predictors standardized prior to estimation.

Table A9.
NTA and Neighborhood Guide

NTA_Code	Neighborhood	Borough	Districts	N_Districts
BX31	Allerton-Pelham Gardens	Bronx	11	1
BX05	Bedford Park-Fordham North	Bronx	10	1
BX06	Belmont	Bronx	10	1
BX07	Bronxdale	Bronx	11	1
BX01	Claremont-Bathgate	Bronx	9, 10	2
BX13	Co-op City	Bronx	11	1
BX75	Crotona Park East	Bronx	12	1
BX14	East Concourse-Concourse Village	Bronx	7, 9	2
BX17	East Tremont	Bronx	10, 12	2
BX03	Eastchester-Edenwald-Baychester	Bronx	11	1
BX40	Fordham South	Bronx	10	1
BX26	Highbridge	Bronx	9	1
BX27	Hunts Point	Bronx	8, 12	2
BX30	Kingsbridge Heights	Bronx	10	1
BX33	Longwood	Bronx	8, 12	2
BX34	Melrose South-Mott Haven North	Bronx	7	1
BX35	Morrisania-Melrose	Bronx	8, 9, 12	3
BX39	Mott Haven-Port Morris	Bronx	7	1
BX41	Mount Hope	Bronx	9, 10	2
BX22	North Riverdale-Fieldston-Riverdale	Bronx	10	1
BX43	Norwood	Bronx	10	1
BX46	Parkchester	Bronx	11	1
BX10	Pelham Bay-Country Club-City Island	Bronx	8, 11	2
BX49	Pelham Parkway	Bronx	11	1
BX52	Schuylerville-Throgs Neck-Edgewater Park	Bronx	8	1
BX55	Soundview-Bruckner	Bronx	8	1
BX09	Soundview-Castle Hill-Clason Point-Harding Park	Bronx	8	1

BX29	Spuyten Duyvil-Kingsbridge	Bronx	10	1
BX36	University Heights-Morris Heights	Bronx	9, 10	2
BX28	Van Cortlandt Village	Bronx	10	1
BX37	Van Nest-Morris Park-Westchester Square	Bronx	11	1
BX63	West Concourse	Bronx	7, 9	2
BX08	West Farms-Bronx River	Bronx	12	1
BX59	Westchester-Unionport	Bronx	8, 11	2
BX44	Williamsbridge-Olinville	Bronx	11	1
BX62	Woodlawn-Wakefield	Bronx	11	1
MN01	Marble Hill-Inwood	Bronx, Manhattan	6, 10	2
BK27	Bath Beach	Brooklyn	20	1
BK31	Bay Ridge	Brooklyn	20	1
BK75	Bedford	Brooklyn	13, 14	2
BK29	Bensonhurst East	Brooklyn	20, 21	2
BK28	Bensonhurst West	Brooklyn	20, 21	2
BK88	Borough Park	Brooklyn	15, 20, 21	3
BK19	Brighton Beach	Brooklyn	21	1
BK09	Brooklyn Heights-Cobble Hill	Brooklyn	13	1
BK81	Brownsville	Brooklyn	17, 23	2
BK77	Bushwick North	Brooklyn	32	1
BK78	Bushwick South	Brooklyn	14, 32	2
BK50	Canarsie	Brooklyn	18, 19	2
BK33	Carroll Gardens-Columbia Street-Red Hook	Brooklyn	15	1
BK69	Clinton Hill	Brooklyn	13	1
BK61	Crown Heights North	Brooklyn	13, 16, 17	3
BK63	Crown Heights South	Brooklyn	17	1
BK83	Cypress Hills-City Line	Brooklyn	19	1
BK38	DUMBO-Vinegar Hill-Downtown Brooklyn-Boerum Hill	Brooklyn	13, 15	2

BK30	Dyker Heights	Brooklyn	20	1
BK91	East Flatbush-Farragut	Brooklyn	17, 18, 22	3
BK82	East New York	Brooklyn	19	1
BK85	East New York (Pennsylvania Ave)	Brooklyn	19	1
BK90	East Williamsburg	Brooklyn	14	1
BK95	Erasmus	Brooklyn	17	1
BK42	Flatbush	Brooklyn	17, 22	2
BK58	Flatlands	Brooklyn	22	1
BK68	Fort Greene	Brooklyn	13	1
BK45	Georgetown-Marine Park-Bergen Beach-Mill Basin	Brooklyn	22	1
BK26	Gravesend	Brooklyn	21	1
BK76	Greenpoint	Brooklyn	14	1
BK25	Homecrest	Brooklyn	21	1
BK41	Kensington-Ocean Parkway	Brooklyn	15, 20, 22	3
BK44	Madison	Brooklyn	22	1
BK43	Midwood	Brooklyn	21, 22	2
BK73	North Side-South Side	Brooklyn	14	1
BK79	Ocean Hill	Brooklyn	16, 17, 23	3
BK46	Ocean Parkway South	Brooklyn	21	1
BK37	Park Slope-Gowanus	Brooklyn	13, 15	2
BK64	Prospect Heights	Brooklyn	13, 17	2
BK60	Prospect Lefferts Gardens-Wingate	Brooklyn	17, 18	2
BK96	Rugby-Remsen Village	Brooklyn	17, 18	2
BK21	Seagate-Coney Island	Brooklyn	21	1
BK17	Sheepshead Bay-Gerritsen Beach-Manhattan Beach	Brooklyn	21, 22	2
BK93	Starrett City	Brooklyn	18, 19	2

BK35	Stuyvesant Heights	Brooklyn	13, 14, 16	3
BK34	Sunset Park East	Brooklyn	15, 20	2
BK32	Sunset Park West	Brooklyn	15, 20	2
BK23	West Brighton	Brooklyn	21	1
BK72	Williamsburg	Brooklyn	14	1
BK40	Windsor Terrace	Brooklyn	15, 22	2
BK99	park-cemetery-etc-Brooklyn	Brooklyn	19, 22	2
MN25	Battery Park City-Lower Manhattan	Manhattan	2	1
MN03	Central Harlem North-Polo Grounds	Manhattan	5	1
MN11	Central Harlem South	Manhattan	3	1
MN27	Chinatown	Manhattan	1, 2	2
MN15	Clinton	Manhattan	2, 3	2
MN34	East Harlem North	Manhattan	4, 5	2
MN33	East Harlem South	Manhattan	4	1
MN22	East Village	Manhattan	1	1
MN21	Gramercy	Manhattan	2	1
MN04	Hamilton Heights	Manhattan	6	1
MN13	Hudson Yards-Chelsea-Flatiron-Union Square	Manhattan	2	1
MN31	Lenox Hill-Roosevelt Island	Manhattan	2	1
MN14	Lincoln Square	Manhattan	3	1
MN28	Lower East Side	Manhattan	1, 2	2
MN06	Manhattanville	Manhattan	5, 6	2
MN17	Midtown-Midtown South	Manhattan	2	1
MN09	Morningside Heights	Manhattan	3, 5	2
MN20	Murray Hill-Kips Bay	Manhattan	2	1
MN24	SoHo-TriBeCa-Civic Center-Little Italy	Manhattan	2	1
MN19	Turtle Bay-East Midtown	Manhattan	2	1
MN40	Upper East Side-Carnegie Hill	Manhattan	2	1
MN12	Upper West Side	Manhattan	3	1
MN35	Washington Heights North	Manhattan	6	1

MN36	Washington Heights South	Manhattan	6	1
MN23	West Village	Manhattan	2	1
MN32	Yorkville	Manhattan	2	1
MN99	park-cemetery-etc-Manhattan	Manhattan	2	1
QN70	Astoria	Queens	30	1
QN48	Auburndale	Queens	25, 26	2
QN76	Baisley Park	Queens	27, 28	2
QN46	Bayside-Bayside Hills	Queens	25, 26	2
QN43	Bellerose	Queens	26, 29	2
QN10	Breezy Point-Belle Harbor-Rockaway Park-Broad Channel	Queens	27	1
QN35	Briarwood-Jamaica Hills	Queens	28, 29	2
QN33	Cambria Heights	Queens	29	1
QN23	College Point	Queens	25	1
QN25	Corona	Queens	24	1
QN45	Douglas Manor-Douglaston-Little Neck	Queens	26	1
QN27	East Elmhurst	Queens	30	1
QN52	East Flushing	Queens	25	1
QN29	Elmhurst	Queens	24	1
QN50	Elmhurst-Maspeth	Queens	24	1
QN15	Far Rockaway-Bayswater	Queens	27	1
QN22	Flushing	Queens	25	1
QN17	Forest Hills	Queens	28	1
QN41	Fresh Meadows-Utopia	Queens	26	1
QN47	Ft. Totten-Bay Terrace-Clearview	Queens	25	1
QN44	Glen Oaks-Floral Park-New Hyde Park	Queens	26	1
QN19	Glendale	Queens	24	1
QN12	Hammels-Arverne-Edgemere	Queens	27	1
QN07	Hollis	Queens	29	1
QN31	Hunters Point-Sunnyside-West Maspeth	Queens	24, 30	2
QN28	Jackson Heights	Queens	30	1

QN61	Jamaica	Queens	28, 29	2
QN06	Jamaica Estates-Holliswood	Queens	26, 29	2
QN60	Kew Gardens	Queens	28	1
QN37	Kew Gardens Hills	Queens	25	1
QN66	Laurelton	Queens	29	1
QN57	Lindenwood-Howard Beach	Queens	27	1
QN30	Maspeth	Queens	24	1
QN21	Middle Village	Queens	24	1
QN51	Murray Hill	Queens	25	1
QN26	North Corona	Queens	24, 30	2
QN42	Oakland Gardens	Queens	26	1
QN71	Old Astoria	Queens	30	1
QN56	Ozone Park	Queens	27	1
QN38	Pomonok-Flushing Heights-Hillcrest	Queens	25, 26, 28	3
QN34	Queens Village	Queens	29	1
QN62	Queensboro Hill	Queens	25	1
QN68	Queensbridge-Ravenswood-Long Island City	Queens	30	1
QN18	Rego Park	Queens	28	1
QN54	Richmond Hill	Queens	27, 28	2
QN20	Ridgewood	Queens	24	1
QN05	Rosedale	Queens	29	1
QN01	South Jamaica	Queens	28, 29	2
QN55	South Ozone Park	Queens	27, 28	2
QN02	Springfield Gardens North	Queens	27, 28, 29	3
QN03	Springfield Gardens South-Brookville	Queens	29	1
QN08	St. Albans	Queens	29	1
QN72	Steinway	Queens	30	1
QN49	Whitestone	Queens	25	1
QN53	Woodhaven	Queens	27	1

QN63	Woodside	Queens	30	1
SI01	Annadale-Huguenot-Prince's Bay-Eltingville	Staten Island	31	1
SI48	Arden Heights	Staten Island	31	1
SI11	Charleston-Richmond Valley-Tottenville	Staten Island	31	1
SI14	Grasmere-Arrochar-Ft. Wadsworth	Staten Island	31	1
SI54	Great Kills	Staten Island	31	1
SI08	Grymes Hill-Clifton-Fox Hills	Staten Island	31	1
SI12	Mariner's Harbor-Arlington-Port Ivory-Graniteville	Staten Island	31	1
SI35	New Brighton-Silver Lake	Staten Island	31	1
SI45	New Dorp-Midland Beach	Staten Island	31	1
SI05	New Springville-Bloomfield-Travis	Staten Island	31	1
SI25	Oakwood-Oakwood Beach	Staten Island	31	1
SI36	Old Town-Dongan Hills-South Beach	Staten Island	31	1
SI28	Port Richmond	Staten Island	31	1
SI32	Rossville-Woodrow	Staten Island	31	1
SI37	Stapleton-Rosebank	Staten Island	31	1
SI24	Todt Hill-Emerson Hill-Heartland Village-Lighthouse Hill	Staten Island	31	1
SI22	West New Brighton-New Brighton-St. George	Staten Island	31	1
SI07	Westerleigh	Staten Island	31	1

Table A10.
Sensitivity of the Homeownership Estimate to Outcome Threshold and Eligible-School Restriction

Sample	**Threshold**	**M3 OR**	**p-value**
All schools	5	1.255	0.004
All schools	10	1.253	0.005
All schools	15	1.248	0.006
Eligible schools	5	1.282	0.018
Eligible schools	10	1.278	0.020
Eligible schools	15	1.266	0.026

Note. The main outcome defines program presence as enrollment of at least 10 G&T-identified students. Alternate thresholds use 5 and 15 students. The eligible-school sample is restricted to schools serving plausible elementary entry grades. Odds ratios are from fully adjusted M3 models and reflect a one-standard-deviation increase in tract-level homeownership.