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ABSTRACT

Immigration and Education: Early Insights from the Buslift to New York City*

Since 2022, New York City has received more than 200,000 asylum-seekers from the southern border, many of whom were young children. Families were placed in homeless shelters, with children subsequently enrolled in nearby public elementary schools. Exploiting variation in homeless shelter capacity across school zones, we show that exposed schools saw increases in migrant students, proxied by English Language Learners, Hispanic students, and students in temporary housing. Despite these shifts, domestic students did not experience adverse impacts on enrollment, test scores, attendance, or chronic absenteeism. Progressive funding helped buffer schools against resource crowding, expanding English language instruction to accommodate newcomers.

JEL Classification: I22, I29, J60
Keywords: immigration, education, asylum-seekers

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1 Introduction

The migration of refugees and asylum-seekers has increased fivefold over the past decade. As 40% of asylum-seekers across the world are young children, such migration poses a growing global challenge for local communities and public school systems receiving such inflows.[1] How school systems absorb migrant children and whether there are effects on the educational attainment of domestic students remain critical issues in understanding the economic impacts of immigration.

Migrant children often require substantial resources, as remedial and multi-lingual instruction may need to be tailored for newcomers (Betts, 1998). If schools are not compensated for these costs, inflows of students from abroad would crowd available resources and, in turn, negatively impact educational attainment (Jackson, 2016; Hyman, 2017; Biasi, 2023). The flight of White and upper-class families away from school districts receiving migrants (e.g., Cascio and Lewis, 2012) could further deprive schools of much needed funds, leaving those remaining to bear a larger burden.

Modern school finance reforms, however, have created progressive systems that often provide schools with additional resources when enrolling students with high-needs, including English Language Learners and students in temporary housing (Hoxby, 2001; Fernandez and Rogerson, 2003). In some designs, progressive funding can respond quickly to unanticipated inflows of newcomers, thereby buffering against resource crowding and learning loss. Hence, whether migrant children crowd resources and impact education outcomes requires deeper investigation.

This paper examines the recent influx of asylum-seekers redirected from border towns to major U.S. cities through a busing program launched by the Texas governor in April 2022. We focus on New York City, which has received the largest volume of migrants among all destinations, totaling over 200,000 to date.[2] Arriving without preexisting living arrangements, migrants were placed into homeless shelters under NYC's unique "Right to Shelter" law, which guarantees same-day shelter for every homeless person requesting refuge, regardless of immigration status.

Nearly 80% of the asylum-seeking population in shelters were families with young children,

[1]Estimates on global refugee migration available from the United Nations High Commissioner for Refugees: https://www.unrefugees.org/refugee-facts/statistics. Statistics on youth asylum-seekers available at United Nations International Children's Emergency Fund: https://data.unicef.org/topic/child-migration-and-displacement/displacement.

[2]The most recent estimates from the NYC Comptroller's Office indicate that as of September 15, 2024, 214,600 asylum-seekers have come through the city's system. Figures are from `https://comptroller.nyc.gov/services/for-the-public/accounting-for-asylum-seeker-services/asylum-seeker-census/`, accessed on October 17, 2024.

predominantly of primary schooling age. We estimate that NYC enrolled 15,000-18,000 new migrant elementary students in the two years after April 2022, almost entirely into traditional zoned public schools.[3] This influx generated a sizable increase in typically high-needs populations – a 54% increase in students in temporary housing and a 12% increase in English Language Learners – and a 5% increase in total elementary enrollments. We refer to this sudden influx of asylum-seekers as the "Buslift" episode for convenience, recognizing that some migrants may have arrived on their own accord outside of the Texas busing program.

We examine how NYC public elementary schools absorbed the sudden, large inflow of migrant children from the Buslift and whether this altered outcomes for non-migrant students. Our empirical strategy exploits variation in the pre-Buslift geographic distribution of homeless shelters across school-zone boundaries. We proxy for the intensity of migrant inflows by using the total capacity of all pre-existing family shelters located within each school's attendance zone. To sharpen comparisons among schools within the same neighborhood, we include zip code-by-year fixed effects in all specifications. A key identifying assumption is that schools with little or no shelter capacity in their zones trace the counterfactual outcome paths that higher shelter capacity schools would have followed in the absence of the Buslift.

Our strategy detects sizable inflows of Buslift children into NYC public elementary schools. While immigrant status is not observed, we document significant increases in enrollment across overlapping categories that closely proxy for recent Buslift arrivals: English Language Learners (ELLs), Hispanic students, and students in temporary housing (STH). Relative to schools without shelters in zone, a school with average shelter capacity experienced an increase of roughly 17 ELLs, about 13% of mean ELL enrollment. Schools with high family-shelter capacity (above the 75th percentile) saw increases of nearly 30 ELLs/Hispanic/STH, approximately a 20% effect over the mean.

Next, we examine impacts on domestic students up to two years after the Buslift. Although the Buslift generated sizable increases in Hispanic enrollments, we find no evidence of corresponding

[3] We combine data on ELLs, students in temporary housing (STH), and children in the NYC homeless shelter system. ELL enrollments in elementary schools grew by 11,000, whereas enrollment of STH grew by 20,000. Data from the Department of Homeless Services indicate that the population of children under age 13 in shelters grew by 16,000. Furthermore, the NYC Comptroller's office released data from November 2022 showing that NYC schools received a total of 5,500 students from families seeking asylum. A linear extrapolation to April 2024 yields an estimated total number of 22,000. About 84% of youth in shelter are of primary schooling age. Together this would yield an estimate of 18,000 ($\approx 22,000 \cdot 0.84$). Hence, we ballpark an inflow between 15,000 and 18,000.

declines among White, Asian, or Black students, with confidence intervals ruling out one-for-one crowd-out. Estimates for total enrollment similarly show no substantial displacement of domestic students, though they are noisier and only some specifications can rule out one-for-one crowd-out. Further analyses on statewide test scores, attendance and chronic absenteeism do not detect significant deleterious effects on non-migrants. Hence, the overall patterns provide little evidence of large negative impacts of migrant students on the educational outcomes of domestic students.

Finally, we show why impacts are muted: NYC's progressive funding formula shields schools from large resource declines. Back-of-the-envelope calculations indicate that, under a traditional formula with no weights for high-needs students, the average school would have lost roughly $1,500 per student. Running the same simulation through NYC's Fair Student Funding (FSF) formula yields only a $15 per-student drop, since schools enrolling migrant students receive additional funds. Although allocations are set at the start of the academic year, NYC adjusts funding twice during the school year, allowing resources to respond quickly to unexpected enrollment fluctuations. State and federal programs (e.g., Title I, Title III) also provided compensatory increases for English learners and students in shelters, thereby reinforcing this buffer.

Empirical analysis of school funding and spending corroborates the capacity of progressive funding to buffer against migrant shocks. We find statistically significant increases in funding for ELLs, which then manifested in greater spending on English-as-a-Second-Language instructors. As a result, pupil-teacher ratios remained unchanged. Progressive funding allowed schools to expand instructional capacity for newcomer students and limit the diversion of resources from domestic students. Because resource buffering does not rule out other channels, we also examine potential peer or social-interaction effects using parent/teacher surveys and find no systematic changes in perceptions of the school environment, though this margin warrants further study with richer data.

Our results are robust to a variety of identification concerns. We implement multiple checks and sample refinements to address potential violations of parallel trends (Roth, 2022; Rambachan and Roth, 2023). Because the Buslift followed the COVID-19 period—during which NYC was the national epicenter—we test whether lingering pandemic effects contaminate our estimates. The results hold when controlling for pandemic-induced out-migration and when further restricting comparisons to geographically close schools that experienced similar pandemic shocks. Finally, our findings are robust to a synthetic difference-in-differences approach (Arkhangelsky et al., 2021) that uses all public elementary schools in New York state to form a synthetic counterfactual.

We contribute to the literature on immigration and education, which shows that inflows can alter both the marginal benefits and marginal costs of schooling (Betts, 1998; McHenry, 2015; Hunt, 2017; Gunadi, 2025). Immigrant workers may raise the returns to education by lowering less-skilled wages, while immigrant students may raise the marginal cost of schooling by diluting resources per pupil. Prior work finds these channels can induce White flight to private schools (Betts and Fairlie, 2003; Cascio and Lewis, 2012). We show that modern, progressive school-finance systems can buffer against resource crowding – at least in the short run.

Recent papers attempting to hone-in on the effects of immigrant student peers, often utilize variation in the presence of immigrant students across grades, within schools (Cortes, 2006; Diette and Oyelere, 2017; Conger, 2015; Figlio et al., 2023; Ballis, 2023). These findings have generally been mixed.[4] It is important to note that due to design, these studies abstract from overall changes in school resources. We complement this work by bringing greater focus to the role of school resources in mitigating the consequences of immigration shocks (Schwartz and Gershberg, 2000; Schwartz and Stiefel, 2004). We aim to provide causal evidence on this relationship by exploiting the unanticipated surge in Buslift migrants to NYC and their eventual placement across homeless shelters, similar in spirit to research on the labor market effects of unanticipated surges in immigration (e.g. Card, 1990; Borjas, 2017; Peri and Yasenov, 2019; Clemens and Hunt, 2019; Anastasopoulos et al., 2021).

Lastly, we inform broader research on the effects of school finance reforms in the United States (e.g., Hoxby, 2001; Fernandez and Rogerson, 2003; Jackson, 2016; Hyman, 2017), and the general equilibrium responses that immigration may incur on school systems (Coen-Pirani, 2011; Cabrales et al., 2018). Apart from more equitable distributions of resources across school districts, we demonstrate that progressive funding systems can help cushion against unanticipated enrollment shocks to schools. As a result this shifts the incidence of shocks, like unanticipated inflows of immigrants, away from domestic students and toward the tax base or reduced funding for other public programs.

To our knowledge, this project is the first to empirically document and study the recent migrant

[4]Evidence from Europe has also not reached a consensus on immigrant peer effects. Bossavie (2020) and Yao et al. (2016) find no evidence of negative peer effects of immigrant children on natives in the Netherlands, while Geay et al. (2013) reports similar null effects in England. Conversely, Tonello (2016) and Jensen and Rasmussen (2011) document adverse effects in Italy and Denmark, respectively. In Georgia and Turkiye, Morales (2022) and Tumen (2021) find evidence of positive school performance effects, and Çakır et al. (2023) finds increased school enrollment among boys.

influx to NYC and its impacts on public education. We recognize that the Buslift may not be a representative case as NYC is the largest public school system in the nation. As such, our findings may be limited in the extent to which they extrapolate to other settings. However, salient episodes like the Buslift may influence attitudes and beliefs about immigration across the nation. Elucidating the effects of migrant inflows within public schools in New York City may inform a wider understanding of the economic impacts of immigration.

The paper proceeds in Section 2 with a description of the Buslift to NYC and the subsequent inflow of migrants to shelters and schools. We also describe NYC's progressive funding system and conceptualize how it buffers against resource crowding following an influx of migrants. Section 3 describes our empirical strategy, data, and discusses identification concerns. Section 4 presents results on migrant and non-migrant enrollment, Mathematics and English Language Arts (ELA) statewide exam scores, and attendance/absenteeism. Section 5 examines mechanisms, including effects on school resources and spending, and parent/teacher perceptions of the school environment. Section 6 concludes.

2 Empirical Setting

2.1 The Buslift

The Buslift migration episode began in early April 2022, when President Biden announced the repeal of Title 42, a pandemic-era policy that allowed the removal of migrants crossing the border without standard asylum proceedings. A large backlog of asylum-seekers, waiting in northern Mexico, subsequently began crossing the border. Several factors likely amplified the migration surge, including the crisis in Venezuela, pandemic downturns across South/Central American economies, and a strong US labor market.

By mid-April 2022, the Governor of Texas enacted a program to bus migrants from border towns (e.g., Del Rio, Brownsville, etc.) to selected cities: Washington D.C., Chicago, Denver, Philadelphia, Los Angeles, and New York City. Among all destinations, New York City has received the largest number of such asylum-seekers, with more than 200,000 having arrived on chartered buses. Many arrived without living arrangements and were placed into homeless shelters across the city, in accordance with NYC's "Right to Shelter" law.

Data from the NYC Department of Homeless Services (DHS) reveals significant increases in the shelter population beginning in mid-April 2022, which city officials have attributed to the inflow of asylum-seeking migrants. The shelter population doubled in 18 months, rising from approximately 45,000 in April 2022 to nearly 90,000 in December 2023 (see Figure 1a). The scale and pace of these inflows were substantial, averaging 75 new individuals per day, with peak periods exhibiting spikes of up to 500 new residents per day. The large increase was primarily driven by Hispanics (see Figure 1b), consistent with the large-scale arrival of asylum-seekers from South and Central America.

Children in families were the most populous group and exhibited significant growth (Figure 1c), more than doubling, from 15,000 in early April 2022 to 33,000 by December 2023. The large increase in children was driven by those of primary schooling age (Figure 1d) – the very young (ages 0-5) and those between ages 6-13 grew from 14,000 in April 2022 to over 30,000 by November 2023. While teenagers (ages 14-17) also saw a modest increase, their numbers remained considerably lower, growing from about 2,000 to 5,000.

The Buslift episode slowed by the start of 2024 (see Figure 1). Various city measures reduced the inflow of migrants during the latter half of 2023, which included executive actions to curtail charter buses transporting migrants, and limits on the duration of stays in shelters.[5] President Biden's June 2024 executive order halting crossings along the southern border effectively ended the Buslift episode.

As a final point, the Buslift occurred in the wake of the COVID-19 pandemic, a period marked by substantial outmigration and declining school enrollments in NYC. As shown in Figure A1, elementary enrollment fell 9 percent from Fall 2019 to Fall 2021, with White students experiencing the steepest decline of more than 14 percent. By 2023–24, asylum-seekers helped produce the first enrollment increase in eight years, reflected in rising counts of ELLs and Hispanic students. These dynamics frame our setting, and our empirical strategy explicitly incorporates checks to account for pandemic-related disruptions and outmigration.

[5]For example, in October 2023 the city announced limits on the duration of families staying in shelters to 60-days, after which families would either need to move to permanent housing, or reapply for shelter. In December 2024, the city required charter buses carrying migrants to provide notice in advance of arrival (see https://www.nyc.gov/office-of-the-mayor/news/538-003/emergency-executive-order-538. Mexico also took measures to reduce inflows by busing migrants near the border to the south of Mexico (see https://www.nytimes.com/2024/05/14/world/americas/mexico-migrants-busing-border.html). Comparable analysis performed by the NYC Comptroller's Office similarly found that growth in all other city funded emergency shelters and other supportive housing decelerated at the end of 2023. See, https://comptroller.nyc.gov/services/for-the-public/accounting-for-asylum-seeker-services/asylum-seeker-census/.

2.2 Placement in Homeless Shelters

Many asylum-seekers lacked housing arrangements and were provided refuge within the homeless shelter system under New York City's "Right to Shelter" law. Initially, existing allocation procedures were used: individuals first applied at a DHS intake center and then were placed in homeless shelters, if deemed eligible, based on available beds and specific accommodation needs (e.g. families vs. single adults, or individuals with disabilities). Anecdotal evidence indicates that selecting specific locations or moving between shelters was difficult, with successful cases requiring third-party legal advocacy.[6]

The volume of migrants overwhelmed DHS intake centers by the summer of 2022, and intake for asylum-seekers was moved to alternative sites.[7] As the shelter system reached capacity, the city began constructing Humanitarian Emergency Relief and Rescue Centers (HERRCs), with capacity to house thousands in large congregate settings. Families with children were prioritized for DHS shelters, while single adults were typically placed in other facilities and HERRCs. Our analysis accounts for HERRCs that were designated for families with children.

2.3 Allocation to NYC Public Schools

By August 2022, city officials enacted a plan, entitled "Project Open Arms," to help migrant youth enroll in public schools.[8] As such, school attendance rates of children in shelters remained consistently high – above 80% and stable over time – even after April 2022, when migrant families began arriving in shelters (Figure 1e).[9] Furthermore, most migrant families remained in shelters through late 2023/early 2024, as placements into permanent housing were rare (under 3%, see Figure 1f). Altogether, this resulted in an increase of roughly 11,500 ELL students, a 14% increase, between June 2021 and June 2024, which mostly occurred within zoned schools (see Figure A1b).

[6] For further details on the shelter system, see https://www.nyc.gov/assets/dhs/downloads/pdf/path-brochure.pdf. Interviews of homeless shelter residents reveal moving between shelters required legal assistance, see https://legalaidnyc.org/wp-content/uploads/2020/01/FINAL-705939v1_PathMagazin_English2017NewLogo.pdf.

[7] In summer 2022 the Port Authority Bus Terminal became the intake center for buses carrying migrants from Texas. By March 2023, the city opened a dedicated 24/7 intake facility at the Roosevelt Hotel near Grand Central Terminal. For more details see https://www.nyc.gov/assets/home/downloads/pdf/press-releases/2023/asylum-seeker-blueprint.pdf.

[8] Enacted in August 2022, just prior to the start of the 2022/23 academic year, Project Open Arms coordinated with various city agencies to equip migrant students "with the full range of academic, language access, and social-emotional resources to succeed." At pop-up welcome centers, counselors assisted families with navigating school enrollment, support services, and school supplies. See https://www.nyc.gov/office-of-the-mayor/news/607-22/adams-administration-project-open-arms-comprehensive-support-plan-meet-educational

[9] One noticeable decline in attendance occurred during peak months of the COVID-19 pandemic in 2020.

How were migrant children allocated to schools? Project Open Arms states that staff place students in schools "within the vicinity of the shelters that have available seats, especially for MLLs [Multilingual Learners]."[10] In appendix A2, we evaluate ELL enrollment patterns across schools based on their eligibility under each stated criterion: (i) proximity to shelters, (ii) available seats, and (iii) multilingual instruction. Only proximity—measured by the presence of family shelters within zone boundaries—predicts increases in ELLs in Fall 2022 and Fall 2023. ELL enrollments were similar and flat across schools with differing shelter exposure in the years prior to 2022. In contrast, schools identified using available capacity or multilingual-instruction criteria show significant pretrends and do not exhibit increases in ELL enrollment by Fall 2022. These patterns motivate our identification strategy, which leverages the geographic distribution of pre-existing family shelters across school zones.

2.4 Progressive Funding as a Buffer

Before turning to the empirical design, we conceptualize the effects of immigrant students on educational outcomes via school funding/resources. As greater funding improves schooling outcomes (e.g., Jackson, 2016; Hyman, 2017; Biasi, 2023; Jackson and Mackevicius, 2024), the effects of new immigrant students will largely depend on how they affect per-student resources. In this section we analytically demonstrate how an influx of new immigrants alters resources, under a traditional formula based around property tax revenue, and also under NYC's progressive funding formula.

2.4.1 A Traditional Formula

To fix ideas, consider a traditional school finance system that primarily relies on property tax revenue.[11] For illustrative purposes, consider an over-simplified formula that determines funding, F, at each school, s, solely based on property tax revenues, calculated by multiplying the property

[10]Discussions with the NYC Comptroller's Office (March 3rd, 2025) indicate that placement procedures were not codified beyond the basic Project Open Arms documents. For details see https://www.nyc.gov/assets/home/downloads/pdf/press-releases/2022/OpenArms-Families-Seeking-Asylum.pdf & https://www.nyc.gov/office-of-the-mayor/news/607-22/adams-administration-project-open-arms-comprehensive-support-plan-meet-educational.

[11]An example of this type of school finance system is that of New Jersey in the early 1990s, which used a linear sum of property tax revenue and a foundation allotment adjusted for local property values and income. See Appendix D of Biasi (2023) for full details.

tax rate (τ) with aggregate local property values (V_s):

$$F_s = \tau V_s \tag{1}$$

Per-student funds, f_s, can be expressed by dividing through by total enrollment N_s and allowing v to denote per-student property values: $f_s = \frac{F_s}{N_s} = \tau v_s$. Given an influx of migrant students to the school, m_s, the change in per-student funds holding constant property tax revenue is: $\frac{\partial f_s}{\partial m_s} = -\frac{F_s}{N_s^2} < 0$. Hence, in this extreme example, immigrants crowd the fixed resources available.[12]

2.4.2 NYC's Fair Student Funding Formula

We now contrast this traditional finance system with NYC's progressive funding formula, known as "Fair Student Funding" (FSF). City funds distributed via FSF account for about two-thirds of school budgets, with state/federal sources making up the remainder. FSF is a weighted student formula, where schools receive funding based on the number and type of registered students. Weights apply to students with various need-types–e.g., individuals with disabilities, English language learners, and those living in poverty–thereby incurring significant progressivity in the formula. We demonstrate how schools sustaining unanticipated increases in immigrants see *greater* funding under FSF, which may buffer against reductions in funds per student and deleterious impacts on domestic students.

The FSF formula that determines the total funds (F^{FSF}) for each school s is the linear sum of three components, as follows,

$$F_s^{FSF} = B + \rho N_s + \sum_i \omega_i \rho N_{is} \tag{2}$$

The first component is known as the "foundation allotment", denoted by B, and is a fixed sum given to each school.[13]

[12]Formally allowing property values to change would yield: $\frac{\partial f_s}{\partial m_s} = \tau \frac{\partial V_s}{\partial m_s} - \frac{F_s}{N_s^2}$, with the resulting impact on resources still being negative if immigrants reduce housing prices ($\frac{\partial V_s}{\partial m_s} < 0$). Monras (2020) finds that immigration is associated with lower property values as immigrants primarily work in construction and reduce building costs. Alternatively, immigrants may increase housing prices, as found by Saiz (2007), which could alleviate resource crowding. It is conceivable to assume that, at least in the short-run, migrants were in shelters and hence had no direct impacts on housing demand and hence prices.

[13]This amount does not vary based on school enrollment or characteristics, and has remained fixed at $225,000 over time.

The second component, which we refer to as the "enrollment allotment", is a variable amount based on registered enrollment. A per-capita dollar amount, denoted by ρ, is given for each student. Multiplying ρ by the number of registered students at school, N_s, yields the total enrollment allotment. While ρ can be adjusted each year, revisions have typically been minor with ρ remaining between \$4,100-\$4,200 over the past decade.

The third component is comprised of funds to students with specific needs. The amount ρ is given to each student that qualifies for particular needs, with need-types denoted by i, and the number of students with a given need-type given by N_{is}. For example, in 2023 there were four broad need-types: (1) students with poor performance needing academic intervention, (2) English Language Learners, (3) students with disabilities and (4) students living in temporary housing. The total amount per student is further scaled up or down by need-type weights, $\omega_i \in (0, \infty)$. Need-types are not mutually exclusive, so that students may count towards multiple need types.

We now derive how an unanticipated influx of immigrants would affect funding per student through the FSF formula. First, we rewrite the formula in per-student terms,

$$f_s^{FSF} = b_s + \rho + \sum_i \omega_i \rho \theta_{is} \tag{3}$$

where f_s^{FSF} denotes FSF funds per student, b_s denotes the foundation allotment per student, and θ_{is} is the share of students of type i in school s. Next, consider an influx of migrants (m) that qualify for a subset M of all need-types I (i.e., $M \subseteq I$). Further, define the complement $M' = \{i \in I : i \notin M\}$ as the subset of need-types that immigrants do not qualify for. Holding enrollment of non-immigrant students fixed for simplicity, the inflow of immigrants affects funds per student as follows,

$$\frac{\partial f_s^{FSF}}{\partial m_s} = \frac{1}{N_s} \left[-b_s - \sum_{i \in M'} \omega_i \rho \theta_{is} + \sum_{i \in M} \omega_i \rho (1 - \theta_{is}) \right] \tag{4}$$

Equation 4 expresses the change in funds per student with respect to an increase in immigrants as the sum of the three terms within the brackets. The first term, $-b_s$, represents the reduction in funding per student as immigrants crowd the fixed foundation allotment. The second term represents the reduction in funding per student due to crowding of the need-based allotment among need-type categories that immigrants do not qualify for $(i \in M')$.

The third term is positive and represents the gain in funding per student due to the increase in the need-based allotment among need-type categories that immigrants qualify for ($i \in M$). Note that each need-type allotment within the third term is scaled by $(1-\theta_{is})$. Schools that do not have students of need type $j \in M$ (i.e. $\theta_{js} = 0$) see the full gain in funds per student from receiving new funds for immigrants with need-type j. At the other extreme where $\theta_{js} = 1$, all students are of need type j, and so new immigrants bring in the same amount of funding as existing students, thereby leaving average funds unchanged.

Whether immigrants raise or lower funds per student then depends on the balance of these three components. Immigrants reduce funds per student if the crowding of the foundation allotment and the need-based allotments that migrants do not qualify for are greater than the gain from need-based allotments that immigrants do qualify for: $b_s + \sum_{i \in M'} \omega_i \rho \theta_{is} > \sum_{i \in M} \omega_i \rho (1-\theta_{is})$. Funds per student do not change when these two quantities are equal, and immigrants would actually raise funds per student when the inequality reverses.

2.4.3 Back of Envelope Changes in Funding

As the literature detects significant negative impacts on learning from a \$1,000 decrease in funds per student[14] , we perform a back-of-envelope calculation of the effects of Buslift migrants on funds per student. We consider an inflow of 30 migrant children–the difference between the 25th and 75th percentiles in the growth of ELL students across schools from 2021 to 2024–into the average elementary school. Under the traditional formula, the inflow of 30 new immigrant students would reduce funding per student by \$1,500, representing a 6% decrease. Under FSF, this inflow would only reduce funds per student by \$15, a 0.05% reduction from baseline funds per student of \$26,500.[15] Hence, the progressivity of FSF may provide a significant buffer against resource crowding.

[14]A meta-analysis by Jackson and Mackevicius (2024) shows that a \$1,000 reduction in spending per pupil for four years reduces test scores by 0.03 standard deviations. Hyman (2017) finds longer-run impacts whereby a \$1,000 reduction in per pupil spending during primary school decreases college enrollment and degree attainment by 3 and 2.3 percentage points, respectively.

[15]We calibrate equation 4, using average school statistics and FSF parameters in 2022: $\theta_1 = 0.75$, $\theta_2 = 0.20$, $\theta_3 = 0.18$, $N_s = 520$, $\rho = \$4,223$, $B = \$225,000$, $\omega_1 = 0.12$, $\omega_2 = 0.40$, and $\omega_3 = 1.36$. We only consider the first three need-type groups–Academic Intervention ($i = 1$), English Language Learner ($i = 2$), and Special Education Services ($i = 3$)–as Students in Temporary Housing was only added in 2023. Traditional formulas are based primarily on property tax revenue. Assuming an inflow of migrants does not affect property tax revenue, at least in the short-run, then the effect on school funding is one of pure crowding – i.e., $\frac{\partial f_s}{m_s} = -\frac{f_s}{N_s}$. Funds per student is roughly \$26,500 at the average school in our sample. Hence, $\frac{\partial f_s}{m_s} = -\frac{\$26{,}500}{520} \approx -\$50$ per migrant. An inflow of 30 migrant students reduces funds per student by \$1,500.

3 Empirical Strategy & Data

We develop several strategies to assess the impacts of Buslift migration on public schools in NYC. Our preferred approach exploits the pre-existing geographical distribution of family-designated homeless shelters across public elementary school zones. We use the total capacity of all family shelters within a school's zone as a continuous measure of treatment, thereby capturing the relative intensity of migrant inflows solely attributable to the predetermined geographical situation and total count of family units within homeless shelters within a school's zoning boundary. This enables us to compare how various school outcomes change over time across schools with higher and lower shelter capacity.

We operationalize this continuous difference-in-differences/event study model using the following empirical specification:

$$Y_{s\eta t} = \alpha + \sum_{\tau \neq p} \beta_\tau \left(Capacity_s \times I[\tau = t] \right) + \gamma_s + \gamma_{\eta t} + X_{s\eta t} + \varepsilon_{s\eta t} \tag{5}$$

$Y_{s\eta t}$ represents an outcome for school s, in neighborhood η, at time t. $Capacity_s$ represents the total capacity (measured in hundreds) of family-designated homeless shelters located within the zoning boundary of school s. We interact this continuous measure of treatment intensity with time-period indicators so that β_τ captures the change in Y for an additional hundred units of family shelter capacity within zone in time period τ *relative* to the reference time-period p. As is standard in event study designs, we set p as the period just prior to the start of the Buslift in April 2022. To assess magnitudes, we modify 5 to only estimate post-period coefficients – i.e., a difference-in-differences model that separately reports coefficients for each post-year.

Simple comparisons across schools with higher versus lower shelter capacity may be confounded by other differences that are typically found in areas with and without shelters, such as socioeconomic status and/or demographic composition. As such, equation 5 includes school fixed-effects (γ_s) to account for fixed differences across schools, and neighborhood-by-year fixed effects ($\gamma_{\eta t}$) to control for neighborhood-specific shocks. Our preferred specification uses zip codes to define neighborhoods, and our results are robust to alternative neighborhood delineations.

Restricting comparisons to schools within the same neighborhood also reduces concerns about the lingering impacts of the COVID-19 pandemic. Schools within the same neighborhood likely experienced similar degrees of learning loss and enrollment declines due to out-migration, an assumption that we examine through careful assessment of pre-trends in outcomes. In addition, we demonstrate our results remain robust through a variety of sample refinements and robustness checks, including controls ($X_{s\eta t}$) that directly capture pandemic era enrollment losses due to out-migration.

We complement this by adopting a second strategy that focuses on schools most likely to be highly affected by this episode. Specifically, we replace the continuous treatment measure in equation 5 with a binary treatment indicator, $Hi\ Capacity_s$, equal to 1 for schools whose family shelter capacity (within zone) is greater than the 75th percentile of all schools with shelters in zone. This identifies a set of 24 schools that likely received a large number of migrant students given the large number and capacity of shelters nearby.

Finally, we implement synthetic differences-in-differences (Arkhangelsky et al., 2021), using data-driven methods to identify appropriate control units. As this requires binary treatment, we use the same set of 24 schools with high shelter capacity in zone as described above. The donor pool includes all public elementary schools in New York State, which facilitates the tracking of enrollment outcomes within schools over time. We describe this procedure in detail in online appendix A3

3.1 Data, Measurement and Sample Descriptives

The sample comprises 600+ public, zoned elementary schools in NYC over the 2018/19 – 2023/2024 school years. We detail the datasets used to measure shelters, identify school zones, and analyze enrollments, test scores, and other outcomes. We then present descriptive statistics of our analysis dataset. Data on school funding are described later in Section 5.

School Zone Shelter Capacity

Constructing our continuous ($Capacity_s$) and binary ($Hi\ Capacity_s$) treatment measures requires merging three data sources. The first is the 2021 Kindergarten Admissions Guide, which provides elementary school addresses. Our second data source, the 2019-20 NYC zone shapefiles, provides zoning boundaries for all NYC schools *prior* to the start of the Buslift. We focus on traditional public elementary schools which comprise 85% of all NYC elementary schools, primarily serve

Kindergarten through 5th grade, and admit students based on residence within zoning boundaries.[16]

Finally, we obtain addresses of NYC homeless shelters from the Department of Homeless Services (DHS) Shelter Repair Scorecard.[17] We use the list of shelters in operation as of February 2022, whose locations were predetermined prior to the start of the Buslift in April 2022. The data also identifies whether a shelter is designated for families or for single adults, and also provides the total capacity of each facility. The union of these three datasets allows us to measure the number and total capacity of family-designated homeless shelters within each school zone.

Figure 2 provides a visual map of NYC homeless shelters and elementary schools, with boundaries reflecting school zones. The green markers indicate public elementary schools and the red triangles represent homeless shelters. Each school zone has one elementary school that serves its residents. Shelters tend to be concentrated in neighborhoods typically characterized by lower socioeconomic status, such as East New York, South Eastern Queens, Southern Bronx, and Upper Manhattan. Hence, our primary design compares otherwise similar schools in the same neighborhood, which only differ in their pre-Buslift exposure to family homeless shelters.

Migrant Enrollment

Publicly available school data do not provide details on immigration status. However, English Language Learners (ELLs) may serve as a useful proxy to capture inflows of new immigrant students. Since the majority of the asylum-seekers came from South and Central America, Hispanic enrollments may also reflect growing migrant student populations. Finally, tracking the number of students in temporary housing (STH) may also reflect increasing enrollments of Buslift migrant youth. Our empirical analyses demonstrate that these overlapping classifications provide a comprehensive way to track the matriculation of asylum-seeking children into NYC public schools.

ELL enrollments are measured in the Fall, and are also disaggregated into three groups based on english proficiency: (1) English as a New Language (ENL) (2) Bilingual and (3) Commanding. We track ELL enrollments for each school from Fall 2018 to Fall 2023 from NYC's Fair Student Funding Detailed Budget data. Hispanic enrollments, from the NYC Demographic Snapshot Data

[16]Private schools and charter schools lack publicly available data across the range of outcomes we explore.

[17]Data obtained from NYC Open Data. While DHS oversees the large majority of shelters in NYC, there exist shelters outside run by charitable organizations and/or other NYC agencies. Data on these shelters are not publicly available.

files, are also available from Fall 2018 to Fall 2023. Data on students in homeless shelters and temporary housing come from the NYC Department of Education's Local Law 73 data, covering counts of students from June 2018 through June 2023. For our synthetic difference-in-differences approach, harmonized enrollment records from the NY State Education Department are available for ELLs, Hispanics, and STH from Fall 2017 through Fall 2023.

Non-migrant Enrollment

To assess non-migrant student enrollment, we use the Demographic Snapshot Data files from Fall 2018 to Fall 2023, which disaggregate enrollments by race. As the majority of asylum-seekers came from South/Central America, tracking the enrollments of Whites, Blacks, and Asians may reveal effects on non-migrant students. Alternatively, we also examine total enrollments and compare this to the increase in migrant enrollment. For example, total enrollment rising by less than migrant enrollment would indicate a decrease in non-migrant students.

Attendance and Absenteeism

Migrant inflows may have deterred non-migrant student attendance, potentially explaining changes in other outcomes. Additionally, peer-to-peer and other within-school spillovers likely depend on the frequency with which migrant students attended school. Hence, we use NYC Department of Education (DOE) data that provides school-level attendance and chronic absenteeism rates, separately for non-ELLs and ELLs, measured for the entire school year from 2018/19 to 2022/23.

Test Scores

Statewide English Language Arts (ELA) and Mathematics exams are administered annually to 3rd-5th graders every April. Data from the NYC DOE provides the number of test takers, average test scores, and the number of proficient students for each school from April 2018 to April 2024. To examine migrant and non-migrant test scores we use these metrics reported for ELL and non-ELL students. Due to data suppression of scores in schools with only a few test-takers, we focus on a subsample of schools whose test scores can be consistently observed over our study period.

Sample Descriptives

Table 1 presents baseline descriptive statistics for our sample. Column (1) shows schools with family shelters in their zone, while column (2) displays statistics for schools without family shelters in their zone. Column (3) focuses on a subset of schools from column (2) that do not have family shelters within their own zone but do have shelters elsewhere in their neighborhood. Column (4) focuses on treated schools under our binary measure, defined as having family shelter capacity in zone greater than the 75th percentile.

NYC elementary schools average around 600 students. Schools with family shelters enroll slightly fewer students than those without. They also serve higher proportions of Black (34% vs. 22%) and Hispanic (49% vs. 37%) students, lower shares of Asian and White students, and higher proportions of students experiencing economic hardship and living in temporary housing, likely reflecting broader socioeconomic variation across neighborhoods. Nonetheless, the share of ELLs, which we consider a close proxy for immigrant status, is quite similar across both school types. One quarter of schools with shelters in zone offer dual language programs, relative to 18% of schools without shelters.

The progressive nature of school funding is evident when comparing columns (1) and (2). Despite lower average performance on ELA and Math statewide tests, schools with family shelters have lower student-teacher ratios and higher per-student funding. Schools have approximately 2 shelters in zone, with 1.5 being family-designated, and an average family shelter capacity of roughly 100. Among schools without family shelters in zone, a small portion (18%) have single adult shelters.

To motivate our within-neighborhood restriction, Column (3) focuses on schools that do not have shelters in their zone, but are located in neighborhoods (zip codes) with shelters. Many characteristics in column (3) are more similar to those in column (1). Column (4) shows that highly exposed schools – those treated under the binary measure – are also quite similar to schools with shelters in zone (column 1). These summary statistics demonstrate that within-neighborhood comparisons (e.g., columns 1 and 4 vs. 3) yield much more similar schools at baseline across most dimensions.

4 Results

4.1 Enrollment

Table 2 presents results on enrollment outcomes, detecting significant increases in migrant students at public elementary schools near shelters. Column (1) displays results for English Language Learners (ELLs) and column (2) shows results for Hispanics. Panels A and B display difference-in-differences estimates on NYC schools using continuous and binary treatments, respectively, and including school and zip code-by-year fixed effects. Panel C displays synthetic difference-in-differences estimates using the same binary treatment as in B, but expands the set of donor schools to include all public elementary schools in NY state. Coefficients for each post-treatment period are presented with standard errors, clustered at the school level, in parentheses and 95% confidence intervals in brackets below.

Our three designs (i.e., continuous treatment, binary treatment, and synthetic DiD) systematically identify significant increases in ELL enrollments in Fall 2022 – roughly 6 months after the start of the Buslift – and even larger increases in Fall 2023 – 1.5 years later. Results for Hispanics, in column (2), mimic those for ELLs, although estimates are noisier for Fall 2022. Further analysis, detailed in online appendix A4, demonstrates that these increases come specifically from ELL students with low levels of English proficiency (i.e., English as a New Language students), and that enrollment of students in homeless shelters also exhibit similar growth.[18]

How large were these increases in migrant enrollment? Our continuous treatment estimates in Panel A which are reported in terms of students per 100 family shelter beds in each school's zone. Average family shelter capacity is 150 beds across schools. Therefore, compared to a school without shelters in its zone, a school with average shelter capacity sustained an increase of 17 ELLs ($\approx 1.5 \times 11.21$) by Fall 2023, an effect size equal to 13% of mean ELL enrollment.

Estimates in Panel B using the binary treatment indicator – schools with family shelter capacity greater than the 75th percentile – show larger increases. This group of highly exposed schools sustained an average increase of 15 ELLs by Fall 2022, and 25 by Fall 2023, representing nearly 20%

[18] Column (1) of Table A1 shows significant increases in enrollment of the least proficient ELL students, "English as a New Language", in Fall 2022 and 2023. There is no detectable change in enrollment of ELL students deemed moderately proficient ("Bilingual" in column 2), or proficient ("Commanding" in column 3). Students in homeless shelters are measured in June of each year, and thus column (5) shows significant increases in their enrollments in June 2023.

of mean ELL enrollment. Hispanic enrollment increases by 11 in Fall 2022 (albeit noisily), and by 30 in Fall 2023. Synthetic DiD estimates in Panel C corroborate these findings, showing increases in ELLs and Hispanic enrollments of 29 and 34 by Fall 2023, respectively.

Having established that our empirical design captures sizable increases in migrant students, the remainder of Table 2 explores impacts on non-migrant enrollments. To proxy for non-migrant students we separately examine enrollments of Whites (column 3), Asians (column 4), and Blacks (column 5). Finally, effects on total enrollments are shown in column (6).

Results do not show significant impacts on enrollment of Whites, Asians, or Blacks. For Whites the coefficients in Panels A and B are negative but insignificant. Confidence intervals, presented in brackets, are tight enough to rule out one-for-one crowd-out.[19] The effects for Asians and Blacks are also imprecisely estimated, with small negative coefficients in Panel A, and small positive coefficients in panel B. Although we can rule out large one-for-one crowd-out effects among each race group, imprecision leaves smaller crowd-out effects as plausible.

To gauge overall effects on non-migrants we analyze total enrollment. Increases in total enrollment of the same magnitude as migrant enrollments would signify no effect on non-migrant enrollment, while no change in total enrollment would reflect one-for-one crowding – the increase in migrant enrollment would be offset by an equivalent decrease in non-migrants. The pattern of results in column (6) reveals positive, but noisy impacts on total enrollment. Panel A shows effects that are positive, but smaller in magnitude than the significant increases in ELLs and Hispanic enrollments in columns (1) and (2). Panel B estimates for total enrollment are very close in magnitude to those for ELLs and Hispanics – total enrollment rises by 12 and 29, while ELLs rise by 15 and 25 in Fall 2022 and 2023, respectively.

Because estimates for total enrollment are imprecise the 95% confidence intervals include 0. Hence, we generally cannot rule out one-for-one crowd-out under standard confidence levels. There are two exceptions worth noting. The first is the effect for Fall 2023 in column (6) of Panel B – the p-value is 0.13, and thus one-for-one crowd-out can be ruled out under an 87% confidence interval. The second is in column (6) of Panel C when using the synthetic DiD approach – the effect on total enrollment in Fall 2023 is significant at the 5% level, possibly due to the larger sample size, and the

[19] For example, the 95% confidence interval lower bound of the effect for Whites in Fall 2023 in Panel A is -7, while the increase in ELLs was 11.21. A one-for-one crowd-out effect would occur if White enrollment fell by 11.21.

95% confidence interval rules out one-for-one crowd-out effects.

Overall, the patterns do not provide strong evidence of large negative effects on enrollment of domestic students, although imprecision limits definitive conclusions regarding smaller sized impacts. Next we examine other possible outcomes, including attendance, chronic absenteeism, and test scores. Before proceeding, however, we first address various potential threats to identification and examine the robustness of our empirical design.

Pretrends

Difference-in-differences estimation requires parallel trends to identify causal effects. Figure 3 displays event study estimates (95% CIs) from equation 5: panels (a)–(c) show ELLs and total enrollment, while panels (d)–(f) show Hispanic, Black, Asian, and White enrollment. Panels (a) and (d) use continuous treatment, (b) and (e) use binary treatment, and (c) and (f) use synthetic DiD. Overall, there are no pretrends evident across these specifications. The patterns mimic our central findings: (i) large increases in ELL and Hispanic enrollments, (ii) similarly sized, but noisy increases in total enrollment, and (iii) no evidence of large displacement of Asians, Whites, and Blacks.

We conduct further testing following recent advances in the literature (Roth, 2022; Rambachan and Roth, 2023). Figure 4 demonstrates that there is no evidence of pretrends when either directly controlling for linear trends, or detrending outcomes – i.e., estimating a linear trend in pre-period data and residualizing this from the entire period (Wolfers, 2006; Kuka et al., 2020; Rambachan and Roth, 2023). Limitations in these approaches are worth highlighting: controlling for linear trends may absorb dynamic treatment effects, and detrending may be biased if the underlying pretrend deviates from the assumed linear form.

Finally, in appendix section A5 we evaluate the extent of pretrend violations under which our results would still hold (Rambachan and Roth, 2023). Our enrollment results on migrants (e.g. ELLs, Hispanics) are robust to modest pre-trend violations, while checks on non-migrant enrollments are less informative given the absence of significant main effects.

Sensitivity Tests

We perform a variety of sensitivity checks that support our empirical strategy: (i) varying binary treatment thresholds, (ii) defining treatment using single-adult shelters, (iii) altering geographic units to define neighborhoods and (iv) removing schools with HERRCs in zone from the analysis. Results indicate that defining treatment using the 75th percentile of family shelter capacity—rather than the 25th, median, or 90th percentiles—strikes a balance between identifying highly exposed schools that sustained large migrant inflows and retaining sufficient numbers of treated units (Table A2). Specifications using the capacity of single-adult shelters to define treatment are not able to systematically detect increases in migrant students (Table A3), supporting our focus on family shelters. Expanding the neighborhood definition to larger geographic units yields similar results, although some pretrends emerge at broader levels, indicating comparisons across dissimilar schools (see tables A4 and A5). Finally, our findings remain similar when removing schools with large HERRCs – congregate housing units to accommodate thousands of asylum-seekers (see Figure 4).[20]

Outmigration

The Buslift episode occurred during New York City's emergence from the COVID-19 pandemic, alongside significant outmigration and learning loss. Our baseline specification already accounts for pandemic-related confounders at the neighborhood level, as we restrict comparisons among schools facing the same lingering pandemic effects in their zip code. Further, our synthetic DiD approach places greater weight on control schools that had similar trends in outcomes prior to 2022. We provide additional evidence that our results are robust to such confounders.

Since the intensity of the pandemic was heavily localized, we further restrict comparisons to schools within the same neighborhood that are within a 1-mile radius of a shelter. We also directly control for outmigration rates from USPS change-of-address data (see appendix A9 for details). Results are robust to both of these robustness checks (see Figure 4).

[20]We obtained the address and designation (single-adults or families with children) of the 17 HERRC facilities via press releases from the Mayor's Office.

Spillovers

Comparisons among physically proximate schools may induce bias due to spillovers – e.g., treatment effects would be overstated if students, teachers, and/or resources move from affected schools to unaffected schools (or vice versa). Nonetheless, our findings are robust to comparisons within geographically larger neighborhoods (Tables A4 and A5) and synthetic DiD that uses all schools in NY state. Additionally, effects reassuringly do not appear to grow in size when further limiting to schools in the same neighborhood that are within 1 mile of shelters.

4.2 Attendance, Absenteeism, and Test Scores

Did the influx of migrants affect student engagement and performance? Table 3 examines impacts on attendance and chronic absenteeism of non-ELL and ELL students. Results do not indicate reduced attendance or increased chronic absenteeism among non-ELL students. In contrast, attendance among ELL students falls by about 0.5 percentage points, while chronic absenteeism rises by roughly 2 percentage points by the end of the 2022/23 school year. This likely reflects compositional changes due to the challenges faced by newly arrived families, including unstable and temporary housing in shelter settings, which impeded regular school participation.

Table 4 reports results for statewide ELA and Math exams taken by 3rd–5th graders. Because test-score data are suppressed when the number of test takers in a school is small, the analytic sample shrinks by nearly half. Hence, we focus on non-ELL exam outcomes. As suppression leaves too few treated schools to support our earlier binary treatment design, we revise the binary treatment design to consider schools with at least one shelter in zone as treated. Estimation on the restricted sample uses inverse propensity score reweighting to correct for potential sample selection.

As the number of test takers is not suppressed, Panel A reports results from the full sample. Panel B shows results on average test scores (standardized) and panel C examines the number scoring proficient on the exams. Results do not indicate significant changes in the number of non-ELL test takers, although point estimates are negative. With respect to test scores, there is no evidence of significant negative impacts either on average scores or the number scoring proficient.

5 School Funding, Resources, and Perceptions

We empirically demonstrate how the progressive nature of NYC school funding helped buffer against more deleterious impacts to enrollments, engagement, and test scores. Importantly, school funding in NYC is designed to respond quickly to enrollment shocks – funds are initially dispersed prior to the start of the school year and two mid-year allocations are given, circa November and February, to help schools account for changing circumstances. To clarify our empirical analysis, we first outline the components of the funding formula, then describe how each responds to increases in migrant enrollment, and finally map these components to their empirical counterparts in the data.

5.1 Full Accounting of School Funds

About half of elementary school budgets comes from NYC's Fair Student Funding formula, while the other half come from NY state and federal sources. Like FSF, state/federal sources also have need-based funding categories (e.g. Title I funds for students in homeless shelters or Title III funds for new immigrants).[21] Hence, a complete accounting of a school's total funds is given as,

$$\begin{aligned} F_s^{Total} &= F_s^{FSF} + F_s^{Other} \\ &= (B + \rho N_s + \sum_i \omega_i \rho N_{is}) + \left(F_{Ms}^{Other} + F_{M's}^{Other}\right) \end{aligned} \tag{6}$$

Total funds (F_s^{Total}) is the sum of FSF funds (F_s^{FSF}) and state/federal funds (F_s^{Other}). The second line expands this by plugging in the expression for FSF funds from 2, and disaggregating state/federal funds into those categories that new migrants qualify for and those that they do not qualify for, maintaining the set notation used earlier – M and M', respectively. Dividing by total enrollment (N_s) yields total funds per student (f_s^{Total}) as the sum of FSF funds per student (f_s^{FSF}) and state/federal funds per student (f_s^{Other}), where the second line breaks these into individual

[21]For full lists and descriptions of funding categories are documented in School Allocation Memorandum: https://infohub.nyced.org/reports/financial/financial-data-and-reports/school-allocation-memorandums.

per-student components:

$$
\begin{aligned}
f_s^{Total} &= f_s^{FSF} + f_s^{Other} \\
&= \left(b_s + \rho + \sum_{i \in M} \omega_i \rho \theta_{is} + \sum_{i \in M'} \omega_i \rho \theta_{is} \right) + \left(f_{Ms}^{Other} + f_{M's}^{Other} \right)
\end{aligned} \tag{7}
$$

The effect of new migrants (m_s) on total funds per student, holding all else constant is:

$$
\begin{aligned}
\frac{\partial f_s^{Total}}{\partial m_s} &= \frac{1}{N_s} \left[-b_s - \sum_{i \in M'} \omega_i \rho \theta_{is} + \sum_{i \in M} \omega_i \rho (1 - \theta_{is}) \right] \\
&\quad + \frac{1}{m_s} \left[\left(\varepsilon_m^{FM} - \theta_{ms} \right) f_{Ms}^{Other} - \theta_{ms} f_{M's}^{Other} \right]
\end{aligned} \tag{8}
$$

In equation 8, the first term in brackets represents the effects on per-student FSF funds described in equation 4. Intuitively, the net effect on FSF funds per student depends on whether the contribution of new migrants students to categories of need-based funds they qualify for ("qualifying categories") outweighs their dilution of funding categories they do not qualify for ("non-qualifying categories").

The second term in brackets captures a similar effect on state/federal funds per student. The net effect depends on whether new migrants' contributions to qualifying categories, $\left(\varepsilon_m^{FM} - \theta_{ms} \right) f_{Ms}^{Other}$, exceeds their dilution of funds from non-qualifying categories, $-\theta_{ms} f_{M's}^{Other}$. The new term, $\varepsilon_m^{FM} = \frac{\partial F_{Ms}^{Other}}{\partial m_s} \frac{m_s}{F_{Ms}^{Other}}$, is the elasticity of state/federal funds from qualifying categories M, with respect to new immigrants m, and $\theta_{ms} = \frac{m_s}{N_s}$ is the existing immigrant share in enrollment. The contribution of new migrants to qualifying categories is weakly positive for any per-student based allocation, $\left(\varepsilon_m^{FM} - \theta_{ms} \right) \geq 0$, consistent with how most state/federal funding categories are distributed.[22]

To summarize, the net effect on per-student funding depends on the extent to which incoming migrants contribute to qualifying categories, which is governed by the progressivity of such funding. This framework also lends itself to empirical implementation as many components of equation 7 are reported in school budgets. Before turning to the data, we note that equation 8 held domestic student responses fixed. Observed funding changes, however, can also reflect shifts in domestic

[22] To prove this consider a general per-student allocation where schools are given \$$A$ per student qualifying for categories in M. Hence, $F_{Ms}^{Other} = AN_{Ms}$, where N_{Ms} is the number of students qualifying for categories in M. The term $(\varepsilon_m^M - \theta_{ms})$ becomes $m_s \left(\frac{A}{F_{Ms}^{Other}} - \frac{1}{N_s} \right)$. Plugging in for F_{Ms}^{Other} yields $m_s \left(\frac{1}{N_{Ms}} - \frac{1}{N_s} \right)$, which is positive so long as the number of students qualifying for categories in M is less than total enrollment, (i.e, $N_{Ms} < N_s$). If all students qualify for categories in M, then the additional migrant does not change the funds per student from qualifying categories.

enrollment—especially among those who qualify for need-based funding. Although earlier analysis found no major changes in non-migrant enrollment, we lack data on domestic students' eligibility for these specific categories. Accordingly, our reduced-form estimates should be interpreted as total derivatives that may incorporate such effects.

5.2 Mapping the Data from School Budget Allocations

We obtain data and empirically assess the following funding components. First, we begin with aggregates from equation 6: (a) total funds per student, f_s^{Total}; (b) FSF funds per student, f_s^{FSF}; and (c) state/federal funds per student, f_s^{Other}. Then we analyze specific components from equation 7: (d) FSF funds per student that immigrants qualify for, $\sum_{i \in M} \omega_i \rho \theta_{is}$; (e) FSF funds per student that immigrants do not qualify for $\sum_{i \in M'} \omega_i \rho \theta_{is}$; (f) state/federal funds per student that immigrants qualify for f_{Ms}^{Other}; and (g) state/federal funds per student that immigrants do not qualify for $f_{M's}^{Other}$.

Publicly available data provides a detailed breakdown of each school's initial FSF allocation, allowing us to measure (b) f_s^{FSF}, (d) $\sum_{i \in M} \omega_i \rho \theta_{is}$, and (e) $\sum_{i \in M'} \omega_i \rho \theta_{is}$ at the beginning of each school year.[23] As there are three general need categories – (i) Academic Intervention, (ii) English Language Learner (ELL), and (iii) Special Education Services – we assign ELL as the category immigrants qualify for and the other two as categories immigrants do not qualify for.[24] The NYC Department of Education's Galaxy database also contain data on other measures at the end of each school year (circa June), which include (a) f_s^{Total}, (b) f_s^{FSF}, (c) f_s^{Other}, (f) f_{Ms}^{Other}, and (g) $f_{M's}^{Other}$.[25]

[23]Data is available from https://www.nycenet.edu/publicapps/Offices/FSF/FSFDetail.aspx. Schools receive their initial FSF funds for each academic year (which begins in September) circa May/June of the academic year prior. We convert FSF funds to per student terms by dividing by enrollment measured in October.

[24]The ELL category provides various different weights for different ELL classifications, including new ELLs, those classified as bilingual, and continuing ELLs. Academic intervention covers several need categories including for students testing below standards. At least initially, new immigrant students are unlikely to meet these criterion as they have not taken statewide tests. Special Education Services contains various weights for students requiring different levels of special education services. A fourth category was added in 2023 for students in temporary housing – we do not separately analyze this category but it is included in the total initial FSF funding amount.

[25]See the NYC Department of Education's online budgeting tool known as Galaxy: https://www.nycenet.edu/offices/d_chanc_oper/budget/dbor/galaxy/galaxyallocation/default.aspx. State/Federal funding categories are numerous and complex in design. Hence, we approximate the categories of non-FSF funds that immigrants qualify for as those from Title I funds for students in temporary housing, Title III funds for limited english proficiency, and Title III funds for immigrants. All other categories are included in the group that immigrants do not qualify for, though in practice immigrants may have qualified for some of these categories.

5.3 Reduced Form Effects on Funding and Resources

We present difference-in-differences estimates of the effects on funding measures in Table 5, focusing on results using continuous treatment for parsimony. Panel (a) displays results on initial FSF funds – i.e, those funds available to the school by the start of the school year in September. Panel (b) displays results for Year-End funds per student, measured in June/July.

First, the coefficient estimates for FSF funding, despite being imprecise, are consistent with the FSF formula providing a buffer. Results in column (1) of panel (a) are not consistent with migrants generating significant declines in initial FSF funds per student in Fall of 2022 or 2023. Further corroborating this are results for year-end FSF funds per student in column (1) of panel (b), which reflect funding after mid-year allocations. Results do not indicate significant negative impacts on year-end funding – in fact the positive and significant coefficient for 2024 indicates that the formula was progressive enough to slightly increase FSF funds per student.

Columns (2) and (3) of panel (a) illustrate that the progressive formula slightly increased FSF funds per student in qualifying categories (i.e. funds for ELLs) and that crowding was not too severe among non-qualifying categories. Panel (b) also show a similar effect for state/federal funds – immigrant qualifying funds saw significant increases (column 3), while non-qualifying categories do not appear significantly impacted (column 4). As a result, total funds per student in column (5) of panel (b) does not appear to significantly decline.

Results provide evidence that the progressive funding allocated extra funds to help buffer against resource crowding. How were these extra resources utilized? Panel (c) of Table 5 explores impacts on teachers/instructors from budget summaries detailing how funds were spent.[26]. Column (1) shows a significant increase in ELL instructors. Column (2) shows no significant change in non-ELL instructors. Total teachers (column 3) do not appear to be significantly impacted, though point estimates are positive. The increase in ELL teachers prevented increases in pupil-teacher ratios as shown in column (4).

[26]Data comes from the Galaxy Budget Spending summaries, available at: NYC DOE Budget Summaries.

5.4 Non-Funding Mechanisms

Inflows of immigrant children may affect domestic/incumbent students via channels unrelated to school funding, for example, through peer effects or social interactions with instructors. In Table A8 we do not find evidence of significant changes in perceptions of school environments from annual surveys given to parents and teachers across 5 broad themes: (1) inclusive leadership, (2) parental outreach, (3) involvement/influence, (4) trust in principal and (5) trust in teachers. Nonetheless, these findings are far from definitive, and further work using granular student-level records is needed to detect peer effects or social interactions.

6 Conclusion

We assess whether the recent influx of immigrant children affected educational outcomes. We focus on NYC, which sustained a large influx of asylum-seeking youth beginning in April 2022. Migrant families were placed in homeless shelters across the city, and children were subsequently enrolled in nearby schools. Our empirical strategy exploits the pre-existing distribution of family-designated homeless shelters across school zoning boundaries, and further restricts comparisons to schools within the same neighborhood.

Analyses focus on the near-term impacts on a range of outcomes, including public school enrollments, attendance/absenteeism, and test scores. We estimate sizable increases in enrollments of likely-migrant students: Hispanics, English Language Learners, and students in temporary housing. Enrollment of other student groups, such as Asian, Black, and White, do not exhibit significant changes. Attendance, absenteeism, and test scores also exhibit little change for non-ELL students.

NYC's progressive school funding formulas help reconcile these near-term findings. Specifically, more dollars are allocated to schools serving needier populations, and hence schools receiving migrant inflows received additional resources to compensate. We substantiate this with empirical analysis on detailed funding and budget data from NYC schools.

This work contributes to elucidating the effects of immigration by studying very near-term responses of local communities to exogenous inflows of migrants. Future work analyzing mid-term and longer-term adjustments would contribute to understanding the dynamics of local educational responses to immigration.

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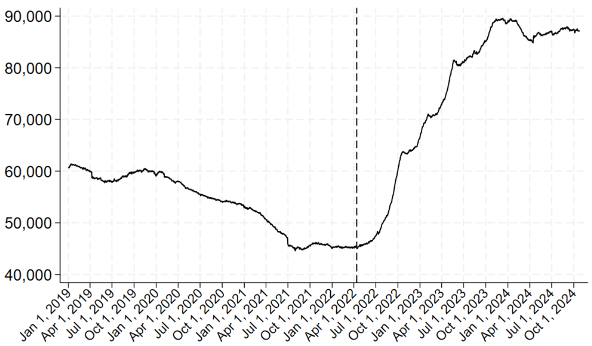
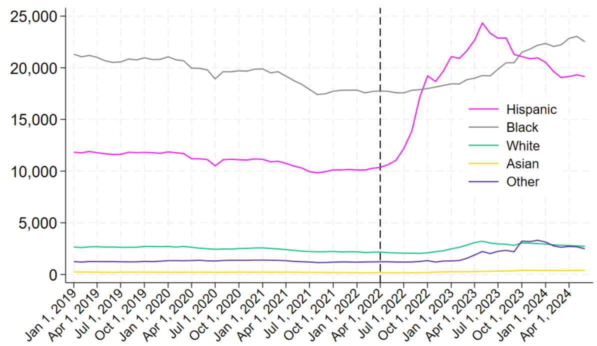
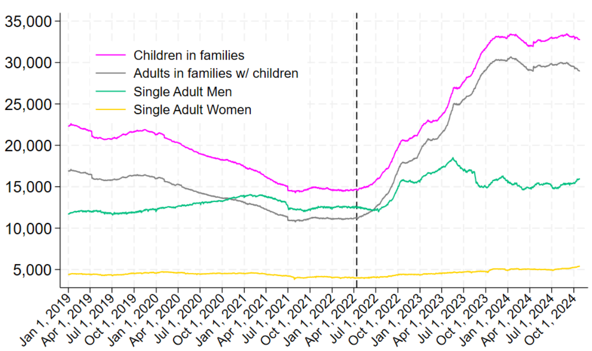
Figure 1: Descriptive Statistics of Individuals in NYC Shelters, 2019-2024



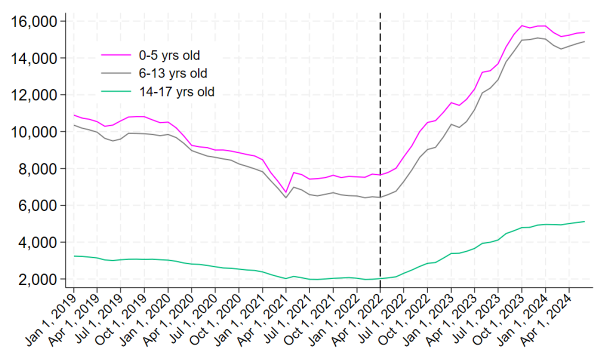
(a) Total Individuals



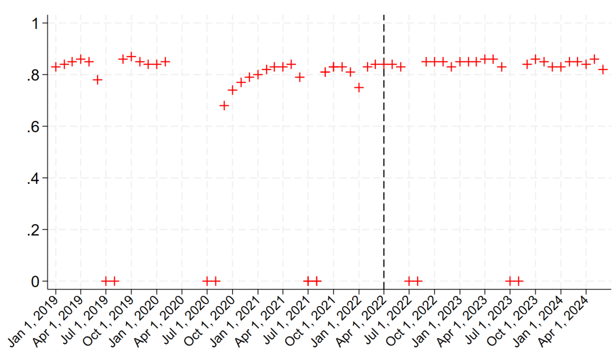
(b) Heads of Household by Race/Ethnicity



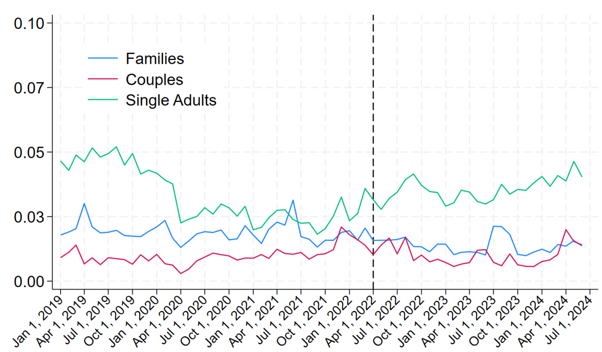
(c) Single Adults, Families, and Children



(d) Children by Age Group



(e) School Attendance Rate



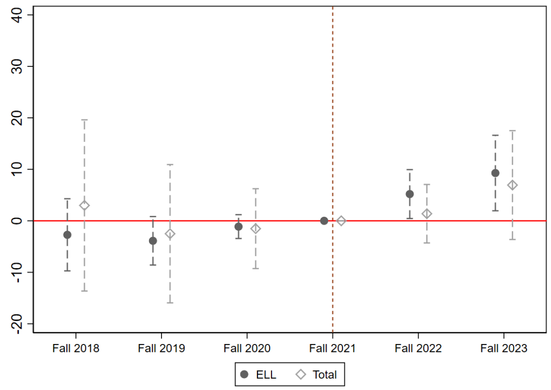
(f) Shelter Exit Rate

Note: Figures show descriptive statistics on individuals in homeless shelters under the New York City Department of Homeless Services (DHS). Total counts of individuals come from the DHS daily logs. Race and age composition come from the DHS Daily Average Census. Data on school attendance rates and shelter exit rates into permanent housing also come from data provided by Department of Homeless Services. All data was obtained via NYC Open Data.

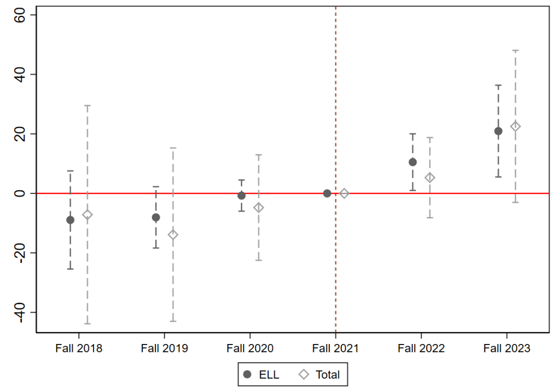
Figure 2: NYC School and Shelter Locations

Note: Map displays homeless shelters, elementary schools, and school zones across NYC. Shelter data are sourced from the Department of Homeless Services' shelter directory, while elementary school locations come from the 2021 Kindergarten Admissions Guide. School zone boundaries are based on 2019–2020 shapefiles. We use the latest available data from NYC Open Data and geocode school addresses to obtain latitude and longitude coordinates.

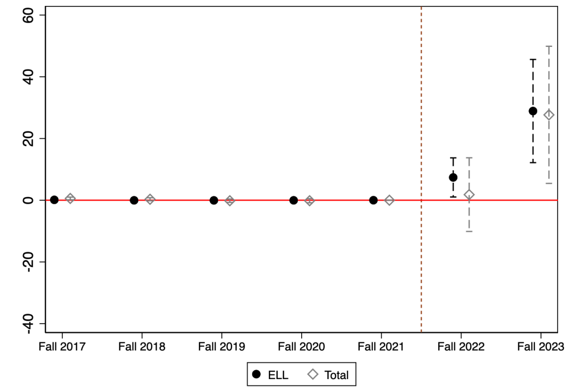
Figure 3: Event Studies for Enrollment Effects



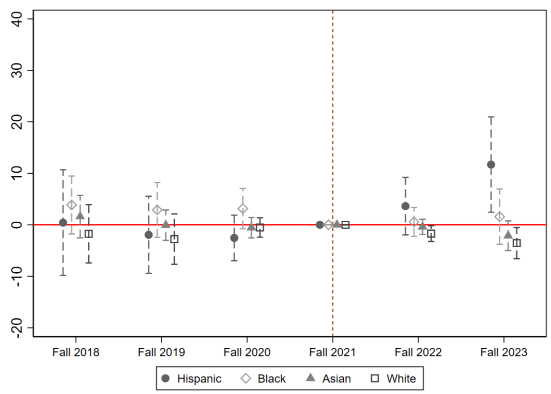
(a) Continuous Treatment: ELL and Total



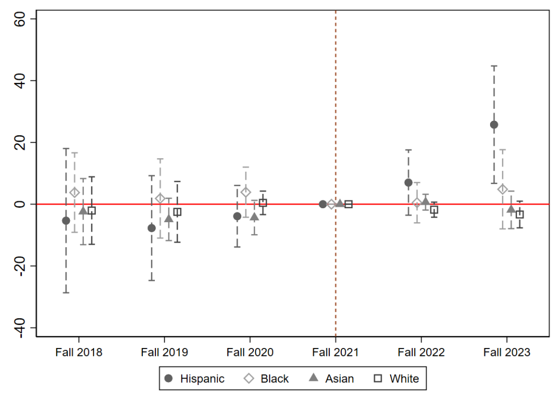
(b) Binary Treatment: Ell and Total



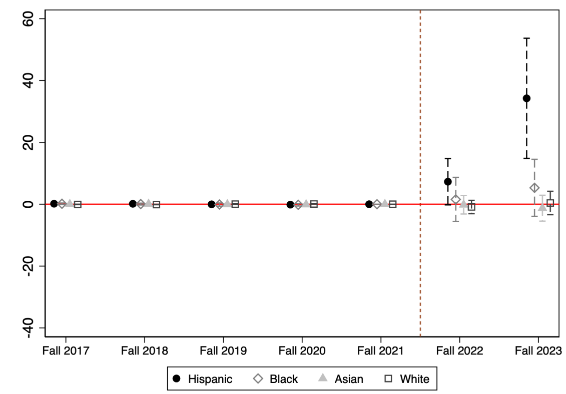
(c) Synthetic DD: ELL and Total



(d) Continuous Treatment: By Race



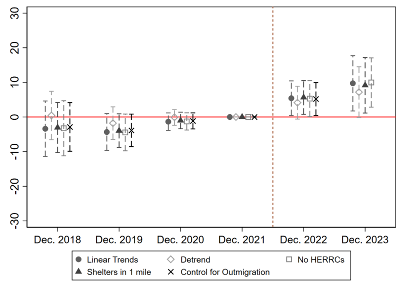
(e) Binary Treatment: By Race



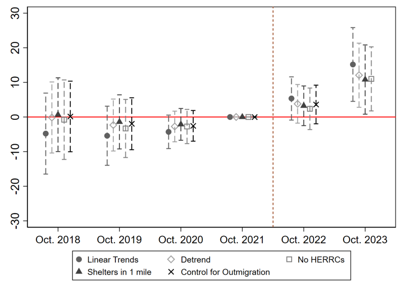
(f) Synthetic DD: By Race

Note: Event studies plot difference-in-differences estimates on fall enrollment outcomes, typically measured around October (except ELLs which are measured in December). Panels (a) and (d) use family shelter capacity as a continuous treatment measure, while (b) and (e) use the binary treatment measure (equal to 1 for schools with family shelter capacity in zone above the 75th percentile of schools with shelters). Panel (c) and (f) use synthetic DiD, drawing on donor public elementary schools across from NY state. Panels (a) and (b) show English Language Learner (ELL) enrollments alongside total enrollment. Panels (c) and (d) show enrollment by race. All specifications include school and zip code-by-year fixed effects. Standard errors are clustered at the school level. Vertical dashed lines indicate 95% confidence intervals.

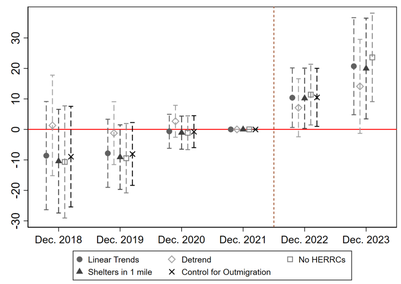
Figure 4: Event Study Robustness for Enrollment



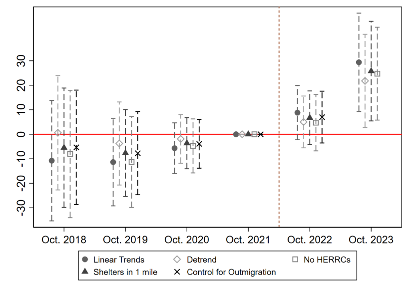
(a) ELLs, Continuous



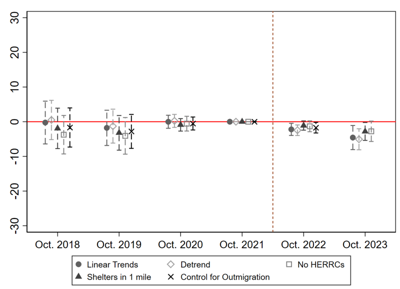
(b) Hispanic, Continuous



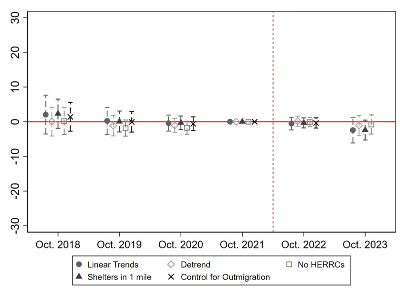
(c) ELL, Binary



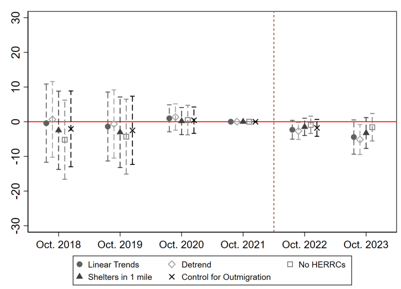
(d) Hispanic, Binary



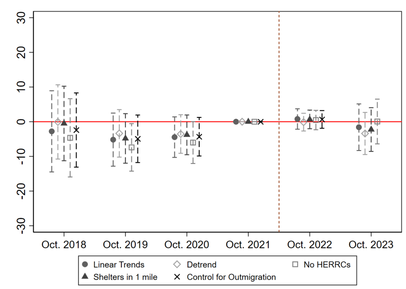
(e) White, Continuous



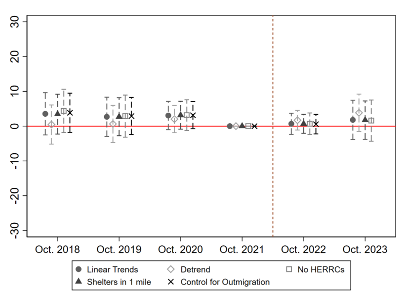
(f) Asian, Continuous



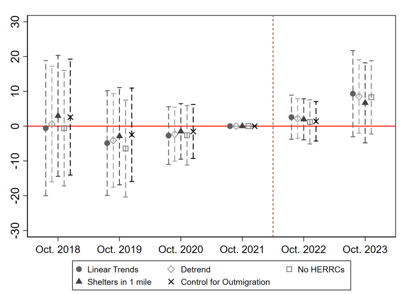
(g) White, Binary



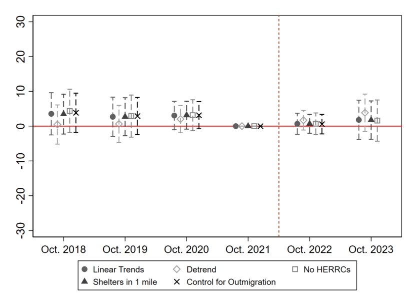
(h) Asian, Binary



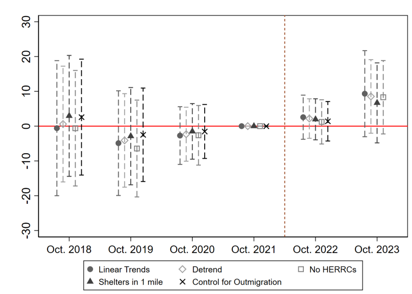
(i) Black, Continuous



(j) Total, Continuous



(k) Black, Binary



(l) Total, Binary

Note: Event study plots show robustness checks for difference-in-differences estimates of enrollment across different student populations. Robustness checks include controls for linear trends, detrending, restricting the sample to schools within 1 mile of shelters, excluding schools near Humanitarian Emergency Relief and Rescue Centers (HERRCs), and controlling for out-migration. Standard errors are clustered at the school level. Vertical bars indicate 95% confidence intervals.

Table 1: Baseline Characteristics of Zoned Public Elementary Schools, 2018/19 - 2019/20

	(1) Has Shelters	(2) No Shelters	(3) Shelters in Neighborhood	(4) Hi Shelters
Total Enrollment	586.26	635.55	600.67	560.56
	(276.86)	(299.15)	(317.20)	(279.85)
% Female	48.75	48.82	48.81	49.11
	(2.55)	(2.51)	(2.66)	(2.43)
% Asian	8.13	17.58	12.41	10.69
	(13.12)	(20.87)	(17.56)	(14.96)
% Black	34.64	22.49	28.46	36.91
	(24.57)	(26.41)	(27.68)	(28.58)
% Hispanic	49.12	37.10	42.57	44.23
	(23.32)	(25.02)	(26.52)	(25.40)
% White	6.06	19.85	13.72	5.55
	(11.22)	(23.06)	(20.09)	(9.29)
% in Temporary Housing	19.81	11.12	14.19	19.44
	(9.44)	(8.57)	(8.66)	(8.78)
% Facing Economic Hardship	83.65	68.72	75.43	81.41
	(14.54)	(24.00)	(22.33)	(14.00)
% English Language Learners	17.40	15.31	15.94	18.09
	(10.05)	(11.29)	(11.46)	(9.72)
Dual Language Program	0.25	0.18	0.23	0.21
	(0.43)	(0.38)	(0.42)	(0.41)
Avg. ELA Score (standardized)	-0.44	0.14	-0.12	-0.41
	(0.75)	(0.95)	(0.93)	(0.60)
Avg. Math Score (standardized)	-0.45	0.17	-0.10	-0.45
	(0.75)	(0.96)	(0.92)	(0.56)
Pupil-Teacher Ratio	12.84	13.64	13.26	12.47
	(2.12)	(2.44)	(2.46)	(1.83)
Funds per Student ($)	24,968.24	23,968.13	24,431.60	25,327.30
	(3,523.83)	(4,125.74)	(4,453.17)	(3,529.12)
Total Shelters in Zone	1.96	0.18	0.31	2.75
	(1.56)	(0.49)	(0.61)	(2.34)
Total Capacity in Zone	142.85	24.09	40.76	301.67
	(153.35)	(72.32)	(90.41)	(226.51)
Family Shelters in Zone	1.51	0.00	0.00	1.96
	(1.05)	(0.00)	(0.00)	(1.50)
Family Capacity in Zone	96.24	0.00	0.00	196.08
	(72.67)	(0.00)	(0.00)	(75.13)
Number of Schools	96	516	305	24

Note: Table presents baseline descriptive statistics for our school sample in academic years 2018/19 and 2019/20. Column (1) shows schools with at least one family shelter in their zone, column (2) shows schools without family shelters, and column (3) shows schools with family shelters in their zip code but not in their school zone. Column (4) shows schools with high family shelter capacity in zone – i.e., family shelter capacity greater than 128, which is the 75th percentile among all schools with shelters in zone. Data are from the NYC Department of Education, NYC Department of Homeless Services, and NYC Open Data.

Table 2: Effects on Enrollment

	(1) ELL	(2) Hispanic	(3) White	(4) Asian	(5) Black	(6) Total
A: Continuous Treatment						
$Capacity_s \times \mathbb{1}[t = 2022]$	7.13**	4.64	-0.44	-0.63	-1.90	1.64
	(2.96)	(4.06)	(1.93)	(1.46)	(2.73)	(6.02)
	[1,13]	[-3,13]	[-4,3]	[-3,2]	[-7,3]	[-10,13]
$Capacity_s \times \mathbb{1}[t = 2023]$	11.21***	12.71**	-2.30	-2.37	-0.89	7.20
	(4.10)	(5.53)	(2.44)	(2.21)	(3.87)	(8.26)
	[3,19]	[2,24]	[-7,2]	[-7,2]	[-8,7]	[-9,23]
B: Binary Treatment						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	14.94**	11.25	-0.75	3.57	-1.89	11.74
	(6.88)	(8.99)	(3.69)	(3.57)	(5.86)	(14.02)
	[1,28]	[-6,29]	[-8,7]	[-3,11]	[-13,10]	[-16,39]
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	25.37***	29.99**	-2.31	1.07	2.45	28.96
	(9.32)	(12.27)	(4.18)	(4.83)	(8.63)	(19.20)
	[7,44]	[6,54]	[-11,6]	[-8,11]	[-14,19]	[-9,67]
Mean Y	129.54	229.09	106.10	114.99	103.77	571.72
N	3,480	3,480	3,480	3,480	3,480	3,480
C: Synthetic DiD with Binary Treatment						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	7.38**	7.27*	-0.90	-0.19	1.55	1.81
	(3.13)	(3.82)	(1.12)	(1.44)	(3.30)	(6.33)
	[1,14]	[-0,15]	[-3,1]	[-3,3]	[-5,8]	[-11,14]
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	28.89***	34.24***	0.40	-1.28	5.30	27.66**
	(7.03)	(9.91)	(2.08)	(1.85)	(4.30)	(11.88)
	[15,43]	[15,54]	[-4,4]	[-5,2]	[-3,14]	[4,51]
Mean Y	53.16	133.65	183.42	45.91	76.73	458.41
N	18,410	18,410	18,410	18,410	18,410	18,410

Note: Table reports difference-in-differences estimates with standard errors (in parentheses) and 95% confidence intervals (in brackets). Outcomes include the enrollment of different groups of students: English Language Learners (col 1), Hispanics (col 2), Whites (col 3), Asians (col 4), Blacks (col 5), and total enrollment (col 6). Enrollments are measured in October of each year. Panel A uses family shelter capacity as a continuous treatment measure. Panel B uses a binary treatment indicator equal to 1 for schools with family shelter capacity in zone greater than the 75th percentile of all schools with shelters in zone. Panel C uses the same binary treatment as in Panel B with a synthetic difference-in-differences estimator drawing from a set of donor schools that includes all public elementary schools in New York State. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

Table 3: Effects on Attendance and Chronic Absenteeism

(a) Continuous Treatment

	(1) Non-ELL	(2) ELL
A: Attendance		
$Capacity_s \times \mathbb{1}[t = 2022]$	-0.003*	-0.003
	(0.002)	(0.002)
$Capacity_s \times \mathbb{1}[t = 2023]$	-0.000	-0.005**
	(0.001)	(0.002)
Mean Y	0.917	0.920
N	2,925	2,925
# Schools	585	585
Pretrends joint test p-value:	0.850	0.503
B: Chronic Absenteeism		
$Capacity_s \times \mathbb{1}[t = 2022]$	0.009	0.012
	(0.008)	(0.011)
$Capacity_s \times \mathbb{1}[t = 2023]$	0.002	0.020**
	(0.007)	(0.009)
Mean Y	0.305	0.298
N	2,925	2,925
# Schools	585	585
Pretrends joint test p-value:	0.907	0.527

(b) Binary Treatment

	(1) Non-ELL	(2) ELL
A: Attendance		
$Capacity_s \times \mathbb{1}[t = 2022]$	-0.005	-0.004
	(0.005)	(0.006)
$Capacity_s \times \mathbb{1}[t = 2023]$	-0.000	-0.009*
	(0.003)	(0.005)
Mean Y	0.917	0.920
N	2,925	2,925
# Schools	585	585
Pretrends joint test p-value:	0.885	0.913
B: Chronic Absenteeism		
$Capacity_s \times \mathbb{1}[t = 2022]$	0.016	0.023
	(0.022)	(0.027)
$Capacity_s \times \mathbb{1}[t = 2023]$	0.001	0.038*
	(0.018)	(0.021)
Mean Y	0.305	0.298
N	2,925	2,925
# Schools	585	585
Pretrends joint test p-value:	0.954	0.419

Note: Table shows difference-in-differences estimates on attendance and chronic absenteeism. The 2020/21 school year is omitted from data due to the COVID-19 pandemic and changes in attendance reporting for in person and virtual schooling. All specifications include school fixed effects and zip code-by-year fixed effects. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

Table 4: Effects on Statewide Exam Performance – Non-ELL students

(a) Continuous Treatment

	(1) Math	(2) ELA
A: Number of Test Takers, Full Sample		
$Capacity_s \times \mathbb{1}[t = 2023]$	-2.51	-3.18
	(3.13)	(3.08)
$Capacity_s \times \mathbb{1}[t = 2024]$	-2.62	-2.89
	(4.03)	(3.90)
N	3,045	3,045
# Schools	609	609
Pretrends joint test p-value:	0.128	0.079
B: Standardized Test Score, Restricted Sample		
$Capacity_s \times \mathbb{1}[t = 2023]$	-0.03	0.04
	(0.07)	(0.06)
$Capacity_s \times \mathbb{1}[t = 2024]$	-0.05	0.07
	(0.07)	(0.07)
N	1,575	1,575
# Schools	315	315
Pretrends joint test p-value:	0.249	0.127
C: Number Scoring Proficient, Restricted Sample		
$Capacity_s \times \mathbb{1}[t = 2023]$	1.88	1.84
	(5.01)	(4.89)
$Capacity_s \times \mathbb{1}[t = 2024]$	-2.22	-0.57
	(5.37)	(5.09)
N	1,575	1,575
# Schools	315	315
Pretrends joint test p-value:	0.928	0.604

(b) Binary Treatment

	(1) Math	(2) ELA
A: Number of Test Takers, Full Sample		
$Capacity_s \times \mathbb{1}[t = 2023]$	-1.71	-2.13
	(3.95)	(3.95)
$Capacity_s \times \mathbb{1}[t = 2024]$	-0.51	-1.53
	(4.96)	(4.95)
N	3,045	3,045
# Schools	609	609
Pretrends joint test p-value:	0.282	0.170
B: Standardized Test Score, Restricted Sample		
$Capacity_s \times \mathbb{1}[t = 2023]$	0.01	0.06
	(0.08)	(0.07)
$Capacity_s \times \mathbb{1}[t = 2024]$	-0.01	0.07
	(0.08)	(0.08)
N	1,575	1,575
# Schools	315	315
Pretrends joint test p-value:	0.472	0.143
C: Number Scoring Proficient, Restricted Sample		
$Capacity_s \times \mathbb{1}[t = 2023]$	3.23	4.02
	(4.32)	(3.88)
$Capacity_s \times \mathbb{1}[t = 2024]$	-1.09	0.39
	(5.30)	(4.89)
N	1,575	1,575
# Schools	315	315
Pretrends joint test p-value:	0.999	0.629

Note: Table shows difference-in-differences estimates on Math and English Language Assessment (ELA) statewide exam outcomes. Exams are given to 3rd-5th graders each April. Panel (a) shows the number of test takers using the full sample of 609 elementary schools reporting data. Panels (b)-(d) use a restricted sample, defined as the 311 elementary schools consistently reporting test scores of English Language Learners and non-ELL students from 2018-2024. We note that tests were not given in 2020 and 2021 due to the COVID-19 pandemic. All specifications include school fixed effects and zip code-by-year fixed effects. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

Table 5: Effects of Buslift on School Funding and Resources

(a): Effects on Initial FSF Funds per Student

	(1) FSF per student	(2) FSF per Student Qualifying Categories	(3) FSF per student Non-Qualifying Categories
$Capacity_s \times \mathbb{1}[\text{SchoolYear2022}-23]$	34.827	2.409	10.461
	(69.743)	(7.083)	(23.552)
$Capacity_s \times \mathbb{1}[\text{SchoolYear2023}-24]$	6.991	12.613*	-30.279
	(72.565)	(7.471)	(20.315)
Mean Y	7,308	305	1,324
Pretrends joint test p-value:	0.522	0.337	0.439
N	3,612	3,612	3,612
# Schools	602	602	602

(b): Effects on Year-End Funds per Student

	(1) FSF per Student	(2) Non-FSF per Student	(3) Non-FSF per Student Qualifying Categories	(4) Non-FSF per Student Non-Qualifying Categories	(5) Total Funds per student
$Capacity_s \times \mathbb{1}[\text{SchoolYear2022}-23]$	-4.907	144.115	74.002***	70.113	139.208
	(30.655)	(156.764)	(21.788)	(152.111)	(159.592)
$Capacity_s \times \mathbb{1}[\text{SchoolYear2023}-24]$	85.128*	-60.411	64.478***	-124.889	24.718
	(48.869)	(228.684)	(21.607)	(218.325)	(250.050)
Mean Y	7,707	9,002	136	8,867	16,709
Pretrends joint test p-value:	0.937	0.405	0.048	0.448	0.500
N	3,612	3,612	3,612	3,612	3,612
# Schools	602	602	602	602	602

(c): Effects on Year-End Teachers

	(1) ELL	(2) Non-ELL	(3) Total	(4) Pupil-Teacher Ratio
$Capacity_s \times \mathbb{1}[\text{SchoolYear2022}-23]$	0.150**	-0.048	0.102	-0.035
	(0.068)	(0.352)	(0.369)	(0.144)
$Capacity_s \times \mathbb{1}[\text{SchoolYear2023}-24]$	0.188*	-0.046	0.143	0.184
	(0.106)	(0.448)	(0.435)	(0.188)
Mean Y	2	33	35	15
Pretrends joint test p-value:	0.507	0.292	0.231	0.019
N	3,612	3,612	3,612	3,612
# Schools	602	602	602	602

Note: Tables show difference-in-differences estimates on fair student funding initial and year-end, and also state/federal and total funds per student. All specifications include school fixed effects and zip code-by-year fixed effects. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

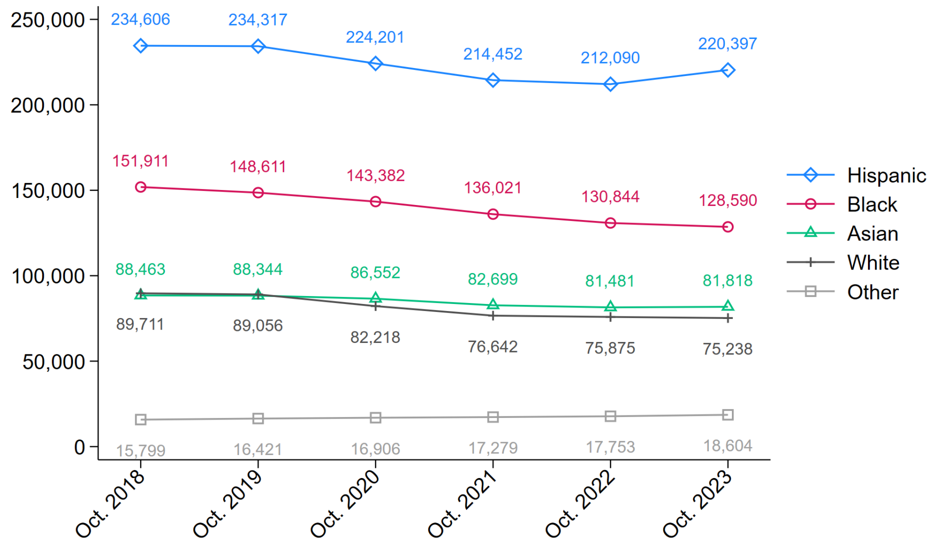
Online Appendix:
“Immigration and Education
Early Insights from the Buslift to NYC”

Selen Ozdogan (CUNY Graduate Center)
Kevin Shih (UC Riverside)

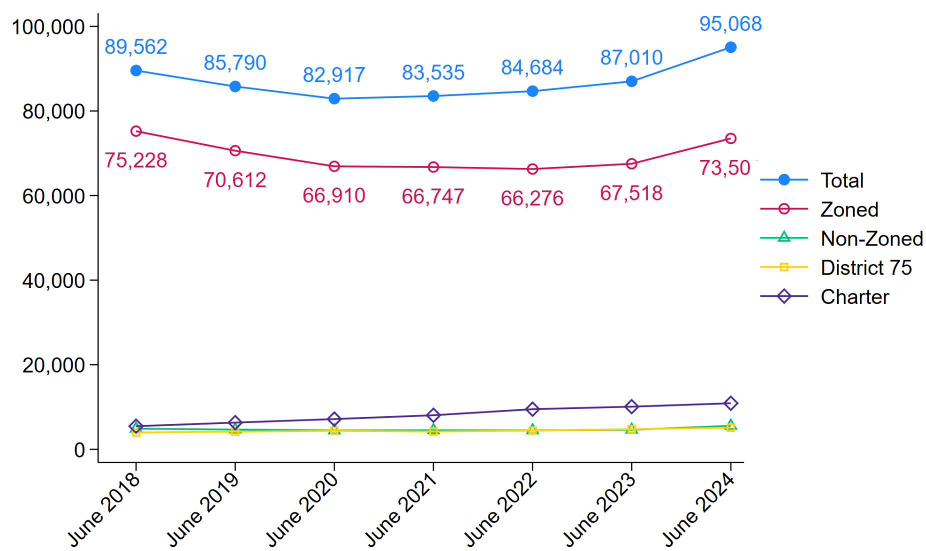
December 22, 2025

A1 NYC School Enrollment Trends

Figure A1: NYC Public Elementary Enrollment Trends, 2018-2024



(a) Enrollment by Race/Ethnicity



(b) English Language Learners by School Type

Note: Figure shows the number of English Language Learner (ELL) students by school type and elementary enrollment by race/ethnicity, obtained from the New York City Department of Education (DOE) annual Demographic Snapshot data files.

A2 Placement to Schools Under NYC's Project Open Arms

How were Buslift migrant children allocated to schools? Project Open Arms outlined that staff identify schools "within the vicinity of the shelters that have available seats, especially for MLLs [Multilingual Learners]."[27] We assess ELL enrollment patterns across schools based on their eligibility in meeting each of these three criteria.

The first criterion specifies proximity to shelters but lacks a clear measure. To address this, we use school zoning boundaries, which provide a well-defined and non-manipulable measure of proximity, increase admission and attendance likelihood, and align with the fact that most NYC elementary students attend zoned schools.[28] Elementary schools are then divided into those with and without DHS family-designated homeless shelters in their zones as of February 2022, just prior to the start of the Buslift.

The second criterion indicates that schools must have available seats; however, New York City only provides recommended capacity limits that are not mandatory. To proxy for available seats at each school, we subtract average class size of each school in 2021 from the recommended class size caps.[29] We then compare schools above the median in terms of this measure of available seats (likely less constrained) to those below the median (likely more constrained). The third criterion recommends placing students in schools with multilingual instruction. To assess this, we classify schools based on whether they offered a dual language program in 2021, prior to the onset of the Buslift episode.

Figure A2 displays the difference in mean ELL enrollment over time, across schools under each of the criterion delineated above. Figure A2a shows differences in mean ELL enrollment at elementary schools with and without shelters in their zone. The figure reveals that mean ELL enrollment between schools with and without shelters is quite similar in the years preceding the start of the Buslift (dashed vertical line). Between Fall 2021 and Fall 2023, ELL enrollment increased by an average of 9 students between schools with and without shelters in zone. Also of note is that

[27] Discussion with the NYC Comptroller's Office (March 3rd, 2025) revealed that procedures and policies regarding the placement of migrants in shelters were not codified beyond basic Project Open Arms documents: see https://www.nyc.gov/assets/home/downloads/pdf/press-releases/2022/OpenArms-Families-Seeking-Asylum.pdf and https://www.nyc.gov/office-of-the-mayor/news/607-22/adams-administration-project-open-arms-comprehensive-support-plan-meet-educational.

[28] A 2019 Senate report found about 70% of U.S. students attend their zoned school.

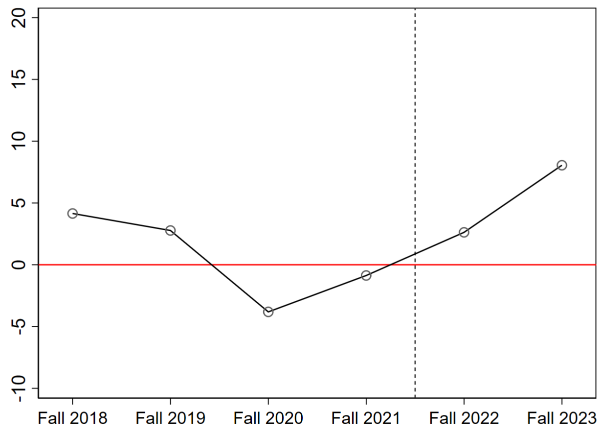
[29] Class size caps are suggested under the United Federation of Teachers' (UFT) collective bargaining agreement. See Figure 1 in the 2023-24 Class Size Reduction Plan.

increases appear both in the Fall 2022 and Fall 2023 periods, 6 months and 1.5 years after the start of the Buslift in April 2022, respectively.

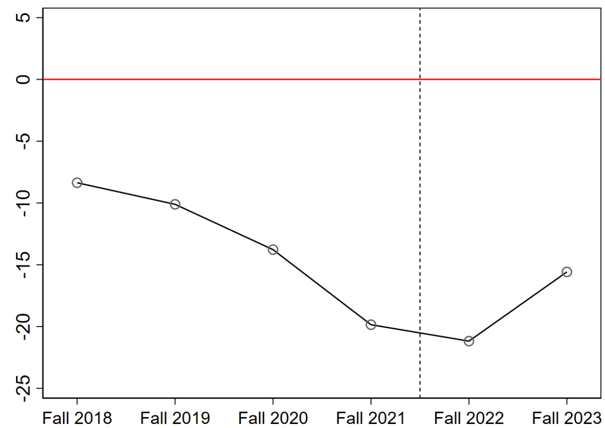
Figures A2b and A2c report mean differences in enrollment for available capacity (defined as having an above median gap between class size caps and average class sizes) and multilingual instruction (defined as having a dual language program). Schools delineated along these criterion appear quite different in terms of pre-Buslift ELL enrollments. Those schools with above median capacity have 10 to 20 fewer ELL students enrolled on average than schools without, and schools with a dual language program have 85-95 more ELL students on average relative to schools without dual language programs. Further, these differences appear to exhibit large downward trends in the Fall 2018 to Fall 2021 period. While there is a noticeable increase in mean ELL enrollments from Fall 2022 to Fall 2023, there is no noticeable change from Fall 2021 to Fall 2022.

These patterns provide insight into the allocation of migrant students and help motivate our empirical strategy. Proximity to shelters, defined by school zoning boundaries, yields an immediate and sustained increase in migrant enrollment, while available capacity and the existence of dual language programs only exhibit a smaller increase from Fall 2022 to Fall 2023 with no immediate changes after the start of the Buslift. Further, the geographical location of shelters is predetermined with respect to schooling outcomes. In contrast, school capacity and dual language exhibit large pre-existing trends in ELL enrollment, which may endogenously reflect changing school outcomes and circumstances in the pre-period. Hence, our identification strategy only leverages the geographic distribution of pre-existing homeless shelters across school zones.

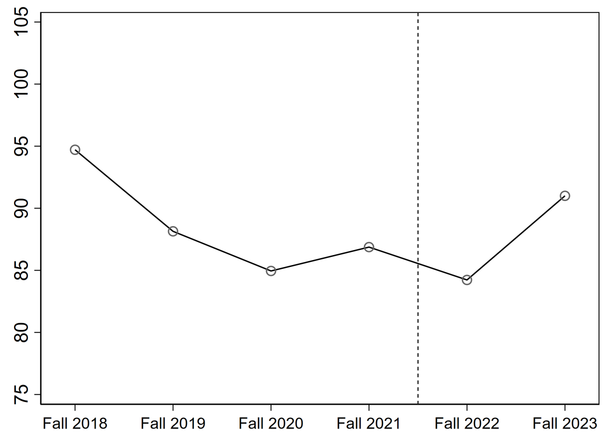
Figure A2: Trends in English Language Learners by Project Open Arms Placement Criterion, 2018-2023



(a) Family Shelters



(b) Available Seats



(c) Dual Language Program

Note: Figure illustrates differences in English Language Learner enrollment trends across schools that have family shelters in their zone, that likely had available seats (proxied by comparing actual class sizes to recommended caps by United Federation of Teachers' collective bargaining agreement), and presence of dual language programs in 2021. Data are from New York City Department of Education, combined with Department of Homeless Services shelter location data.

A3 Synthetic Difference-in-Differences

We obtain enrollment data for all New York state elementary schools outside NYC from the New York State Education Department (NYSED) Enrollment Database covering Fall 2017 through Fall 2023. Enrollment data are reported to the state in October each year, making the Fall 2022 data point the first post-period in this design. The data provide total enrollment (kindergarten through 5th grade), as well as breakdowns by race/ethnicity and English Language Learners (ELLs). Similar to our main design, we exclude private and charter schools, as well as unzoned schools.

We employ a synthetic difference-in-differences (SDID) approach (Arkhangelsky et al., 2021), which combines the advantages of panel difference-in-differences (DID) and synthetic control methods. We estimate the Buslift's causal effect on enrollment outcomes for treated NYC schools using the following equation:

$$(\hat{\tau}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg\min_{\tau,\mu,\alpha,\beta} \left\{ \sum_{s=1}^{N} \sum_{t=1}^{T} (Y_{st} - \mu - \alpha_s - \beta_t - Hi\ Capacity_s \tau)^2 \hat{\omega}_s^{SDID} \hat{\lambda}_t^{SDID} \right\} \quad (9)$$

Y_{st} represents the outcome for school s at time t. The $Hi\ Capacity_s$ indicator equals 1 for city schools with family shelter capacity greater than the 75th percentile among schools with shelters in zone. The causal treatment effect is estimated using a two-way fixed effects (TWFE) model with optimally selected weights $\hat{\omega}_s^{SDID}$ and $\hat{\lambda}_t^{SDID}$.

SDID creates a more flexible approach than the standard TWFE DID design because of this reweighting and matching pre-treatment trends using control units that minimize trend differences before exposure. In addition, SDID provides also robustness check against potential neighborhood spillovers in our primary design. Specifically, our primary analysis compares outcomes among schools within the same neighborhood with varying family shelter capacity in their attendance zones. As such, estimates may reflect spillovers among neighboring schools in close proximity. By modifying the comparison group to include schools from across New York state helps assuage concerns of confounding spillovers.

A4 ELLs by Type and Homeless Student Enrollment

Table A1: Additional Evidence on Migrant Enrollment

	(1) ELLs by Type: English as New Language	(2) ELLs by Type: Bilingual	(3) ELLs by Type: Commanding	(4) Students in Shelters
A: Continuous Treatment				
$Capacity_s^{Family} \times \mathbb{1}[t = 2022]$	7.63***	-0.89	0.38	-0.64
	(2.90)	(1.51)	(0.67)	(2.78)
$Capacity_s^{Family} \times \mathbb{1}[t = 2023]$	12.58***	-0.69	-0.68	10.10***
	(4.17)	(2.09)	(1.06)	(3.72)
B: Binary Treatment				
$Hi\ Capacity_s^{Family} \times \mathbb{1}[t = 2022]$	16.98**	-3.78	1.74	-4.33
	(6.74)	(3.45)	(1.44)	(6.13)
$Hi\ Capacity_s^{Family} \times \mathbb{1}[t = 2023]$	30.51***	-4.50	-0.63	13.71
	(9.56)	(4.99)	(1.86)	(8.83)
C: Synthetic DiD with Binary Treatment				
$Hi\ Capacity_s^{Family} \times \mathbb{1}[t = 2022]$				3.97
				(3.49)
$Hi\ Capacity_s^{Family} \times \mathbb{1}[t = 2023]$				34.77***
				(8.16)

Note: Tables show difference-in-differences estimates on likely migrant enrollment. All specifications include school and zip code by year fixed effects. Columns (1)-(3) disaggregate ELLs into groups determined by administrative assessments of english language ability: (i) English as a New Language, (ii) Bilingual and (iii) Commanding. Column (4) shows results on enrollment of students in homeless shelters and other temporary housing. Panel A shows results using family shelter capacity in zone as a continuous measure of treatment. Panels B and C use binary treatment, defined as family capacity greater than the 75th percentile among schools with shelters in zone, with the latter employing synthetic DiD. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

A5 Parallel Trends

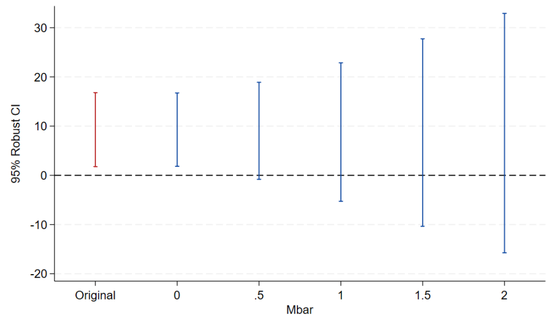
Recent advances in the literature have highlighted shortcomings in standard practice in assessing parallel trends in difference-in-differences designs. In particular, pre-trend tests may be underpowered and conditioning analysis on specifications that pass pretrend tests may induce bias. To address these concerns, we follow recommendations in Rambachan and Roth (2023) and report confidence sets of our estimates under various degrees of parallel trends violations. This transparently reveals the extent of parallel trends violations under which our results remain robust.

We explore two types of trend violations proposed by Rambachan and Roth (2023). The first type bounds the relative magnitude, denoted by $\bar{M}$, by which confounding factors that give rise to pre-treatment trends affect trends in the post-treatment period. Hence, we examine the robustness of our results to situations where post-treatment violations in parallel trends are no greater than $\bar{M}$ times the pre-treatment violation in trends. We use values of $\bar{M}$ from 0 to 2, in increments of 0.5.

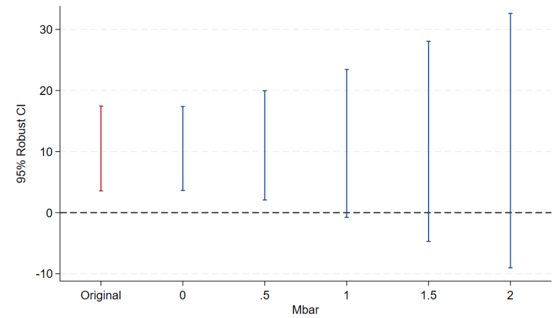
The second type of test, known as smoothness restrictions, restricts changes in the *slope* of parallel trends violations across pre- and post-periods. Here, we again use the notation $\bar{M}$ to denote the maximum percentage deviation in slope across consecutive periods. We evaluate the robustness of our findings to values of $\bar{M}$ ranging from 0 to 2 percentage points (p.p.), in 0.5 p.p. increments.

Results of this exercise are reported in Figures A3 and A4. Figures report 95% confidence intervals of effects on enrollment against values of $\bar{M}$ ("Mbar"). Overall, the pattern of findings indicates that the results on likely migrant enrollment (i.e., ELL, ENL, and Hispanic) are generally robust to post-treatment violations being no greater than the size of pre-treatment violations. In terms of smoothness restrictions, results on migrant enrollment are robust up to a 0.5 p.p. change in slope across consecutive periods. Results for domestic/incumbent student enrollment are less informative, as the main set of results generally did not reveal statistically significant effects.

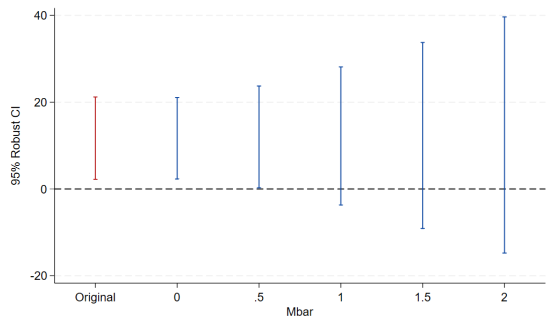
Figure A3: Sensitivity Testing of Pretrends, Relative Bounds



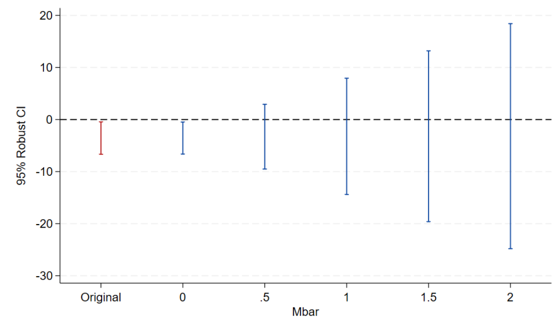
(a) ELLs



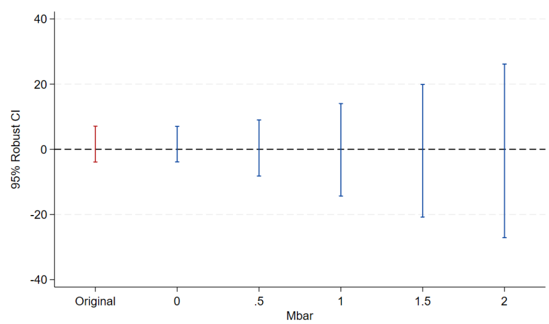
(b) ENL



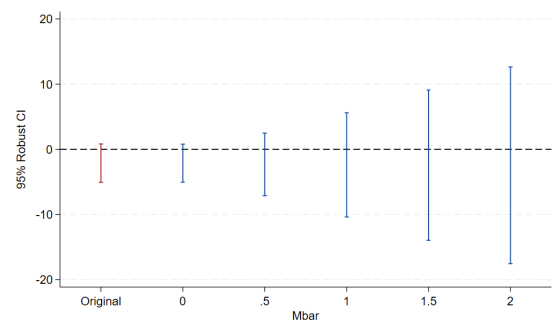
(c) Hispanic



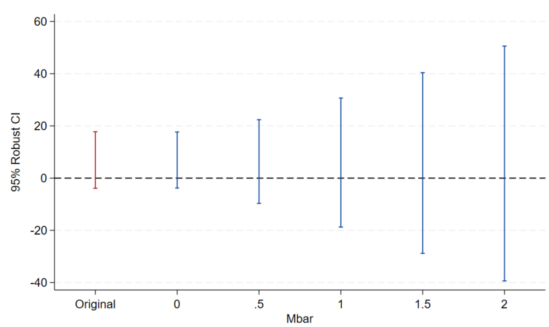
(d) White



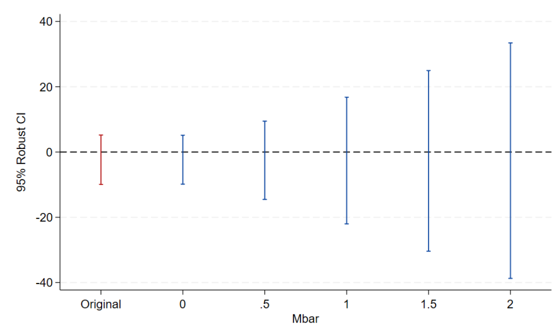
(e) Black



(f) Asian



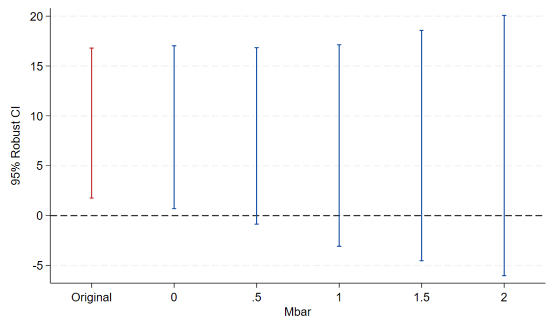
(g) Total



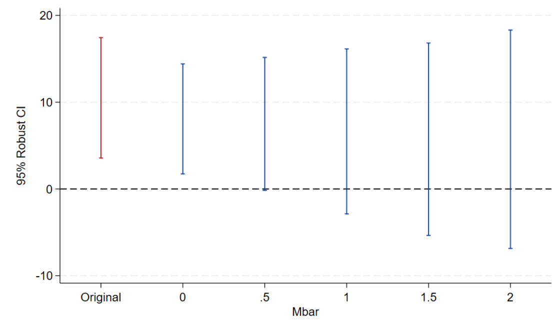
(h) Non-ELLs

Note: Figures report relative magnitude bounds robustness check recommended by Rambachan and Roth (2023) for different student populations. “Mbar” represents the maximum factor by which post-treatment violations can exceed pre-treatment violations. Vertical bars indicate 95% confidence intervals of effects on enrollment against values of “Mbar”. ENL refers to ELL students classified as learning English as a new language.

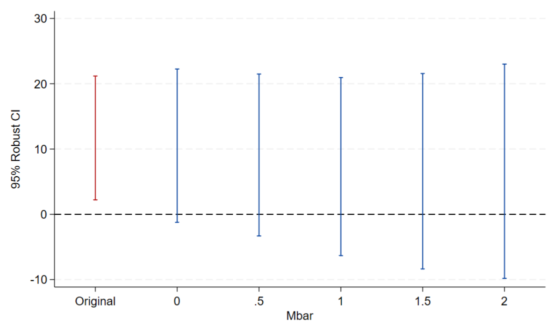
Figure A4: Sensitivity Testing of Pretrends, Smoothness Restrictions



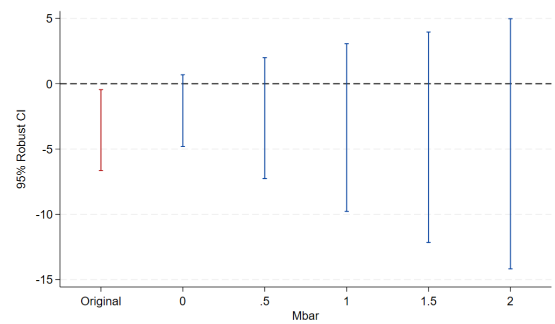
(a) ELLs



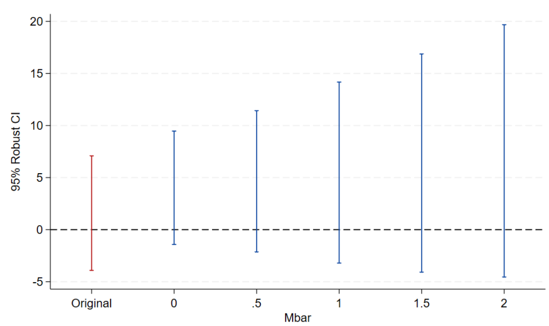
(b) ENL



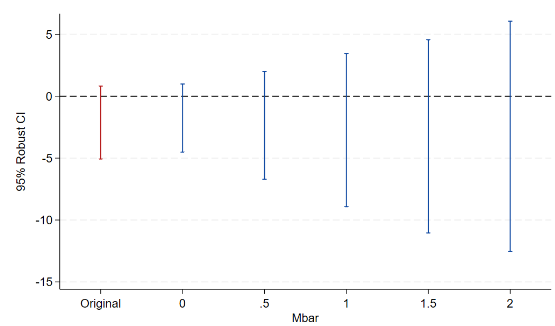
(c) Hispanic



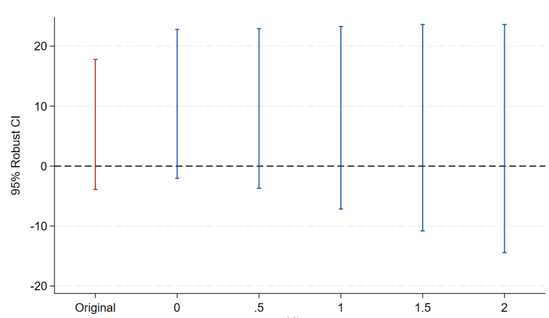
(d) White



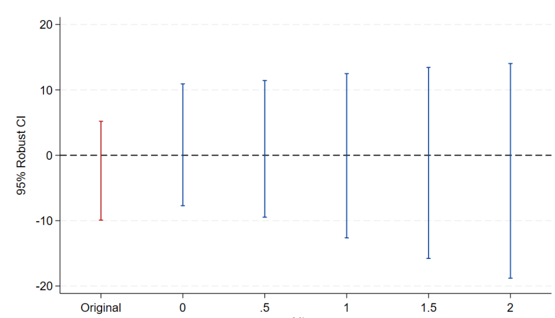
(e) Black



(f) Asian



(g) Total



(h) Non-ELLs

Note: Figures report smoothness restriction robustness check recommended by Rambachan and Roth (2023) for different student populations. "Mbar" represents the maximum change in slope of trend violations across periods. Vertical bars indicate 95% confidence intervals of effects on enrollment against values of "Mbar". ENL refers to ELL students classified as learning English as a new language.

A6 Alternative Binary Treatment Thresholds

Table A2: Effects on Enrollment using Alternative Binary Treatment Thresholds

	(1) ELL	(2) Hispanic	(3) White	(4) Asian	(5) Black	(6) Total
A: DiD with Binary Treatment > 25th percentile, # Treated=72						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	9.38**	11.01*	-1.03	-1.41	-2.27	6.90
	(4.49)	(6.35)	(2.80)	(2.31)	(3.62)	(9.31)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	11.42**	18.36**	-4.30	-4.25	-1.93	9.32
	(5.57)	(8.35)	(3.62)	(3.36)	(4.75)	(11.72)
B: DiD with Binary Treatment > 50th percentile, # Treated=48						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	8.07*	8.73	0.68	-0.07	-7.20*	2.65
	(4.37)	(5.85)	(2.81)	(3.11)	(4.02)	(9.24)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	12.39*	18.89**	-2.15	-1.77	-6.24	10.01
	(6.31)	(8.60)	(3.98)	(3.90)	(5.75)	(12.47)
C: DiD with Binary Treatment > 75th percentile, # Treated=24						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	14.94**	11.25	-0.75	3.57	-1.89	11.74
	(6.88)	(8.99)	(3.69)	(3.57)	(5.86)	(14.02)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	25.37***	29.99**	-2.31	1.07	2.45	28.96
	(9.32)	(12.27)	(4.18)	(4.83)	(8.63)	(19.20)
D: DiD with Binary Treatment > 90th percentile, # Treated=9						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	29.98**	8.91	4.19	-2.35	4.70	15.03
	(14.35)	(20.21)	(7.49)	(4.36)	(10.58)	(28.44)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	37.41**	31.22	0.31	-1.48	12.99	39.81
	(17.53)	(25.71)	(8.06)	(8.57)	(18.06)	(38.20)
E: Synthetic DiD w/ Binary Treatment > 25th percentile, # Treated=72						
$Hi\ Capacity_c \times \mathbb{1}[t = 2022]$	6.43***	6.91***	-0.14	-0.33	1.95	2.30
	(1.59)	(2.27)	(0.74)	(1.06)	(1.72)	(3.31)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	15.28***	17.14***	0.69	-0.55	1.94	8.27
	(3.66)	(4.93)	(1.29)	(1.30)	(2.81)	(5.55)
F: Synthetic DiD w/ Binary Treatment > 50th percentile, # Treated=48						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	6.02**	5.92**	-0.05	-0.23	1.51	1.52
	(2.45)	(2.35)	(1.02)	(1.47)	(2.19)	(4.20)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	17.03***	18.84***	0.66	-0.42	2.63	11.65
	(5.32)	(5.95)	(1.65)	(1.53)	(3.26)	(8.02)
G: Synthetic DiD w/ Binary Treatment > 75th percentile, # Treated=24						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	7.38**	7.27*	-0.90	-0.19	1.55	1.81
	(3.32)	(3.96)	(1.19)	(1.57)	(3.75)	(5.96)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	28.89***	34.24***	0.40	-1.28	5.30	27.66**
	(8.92)	(10.65)	(1.96)	(2.02)	(4.71)	(11.81)
H: Synthetic DiD w/ Binary Treatment > 90th percentile, # Treated=9						
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	13.72*	12.40	-2.11	-3.43	4.75	5.52
	(8.09)	(7.65)	(1.89)	(3.45)	(4.60)	(8.89)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	40.06**	45.61***	-2.21	-6.56**	7.05	33.12*
	(15.56)	(17.32)	(4.66)	(3.30)	(7.70)	(18.58)

Note: Table shows difference-in-differences estimates with binary treatment on enrollment outcomes. All specifications include school and zip code by year fixed effects. Various thresholds for treatment include the 25th, 50th, 75th, and 90th percentile of family shelter capacity among schools with shelters in zone. These correspond to more than 50 beds (25th percentile), 80 beds (50th percentile), 128 beds (75th percentile, and 175 beds (90th percentile). *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

A7 Family, Adult and Total Shelters

Table A3: Effects on ELL Enrollment using Family, Adult, and Total Shelters as Treatment

	(1) Family Capacity Treatment	(2) Adult Capacity Treatment	(3) Total Capacity Treatment
A: Continuous Treatment			
$Capacity_s \times \mathbb{1}[t = 2022]$	7.13**	-0.21	1.51
	(2.96)	(1.33)	(1.08)
$Capacity_s \times \mathbb{1}[t = 2023]$	11.21***	2.57	4.15**
	(4.10)	(2.10)	(1.90)
B: Binary Treatment			
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	14.94**	1.80	8.82
	(6.88)	(6.23)	(5.65)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	25.37***	15.43	22.44***
	(9.32)	(10.42)	(8.27)
C: Synthetic DiD with Binary Treatment			
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	7.38**	4.17*	4.34*
	(3.13)	(2.52)	(2.51)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	28.89***	20.41**	22.61***
	(7.03)	(8.28)	(6.67)

Note: Tables show difference-in-differences estimates on ELL enrollment. All specifications include school and zip code by year fixed effects. Columns (1) shows our main results using family capacity to define treatment. Column (2) shows results using only adult shelters to define treatment. Column (3) shows results when using all shelters (family + adult) to define treatment. Panel A shows results using continuous treatment, while B and C show results using binary treatment (capacity> 75th percentile), with the latter employing synthetic difference-in-differences. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

A8 Defining Neighborhoods

Table A4: Effects on Enrollment using Different Neighborhood Definitions, Continuous Treatment

	(1) Sub-District	(2) Council District	(3) Community Board	(4) Zip Code	(5) NTA
A: English Language Learner					
$Capacity_s \times \mathbb{1}[t=2022]$	5.46**	4.69*	4.15**	7.13**	5.69**
	(2.36)	(2.40)	(1.93)	(2.96)	(2.47)
$Capacity_s \times \mathbb{1}[t=2023]$	11.08***	10.11***	9.43***	11.21***	10.22***
	(3.79)	(3.54)	(2.85)	(4.10)	(3.89)
Pretrends joint test p-value:	0.663	0.408	0.198	0.163	0.483
B: Hispanic					
$Capacity_s \times \mathbb{1}[t=2022]$	3.39	2.50	2.99	4.64	-1.05
	(3.19)	(3.39)	(3.45)	(4.06)	(3.99)
$Capacity_s \times \mathbb{1}[t=2023]$	11.19***	10.20**	11.62***	12.71**	7.04
	(3.93)	(5.07)	(3.90)	(5.53)	(4.83)
Pretrends joint test p-value:	0.200	0.550	0.688	0.254	0.432
C: White					
$Capacity_s \times \mathbb{1}[t=2022]$	2.55*	2.68*	2.92*	-0.44	3.02
	(1.42)	(1.52)	(1.61)	(1.93)	(1.93)
$Capacity_s \times \mathbb{1}[t=2023]$	1.24	1.86	1.62	-2.30	1.14
	(1.85)	(1.85)	(2.02)	(2.44)	(2.09)
Pretrends joint test p-value:	0.033	0.054	0.088	0.234	0.154
D: Asian					
$Capacity_s \times \mathbb{1}[t=2022]$	-1.01	-0.72	-2.62*	-0.63	-1.44
	(1.61)	(1.39)	(1.53)	(1.46)	(1.75)
$Capacity_s \times \mathbb{1}[t=2023]$	-2.01	-1.38	-3.89**	-2.37	-2.99
	(1.69)	(1.68)	(1.85)	(2.21)	(2.22)
Pretrends joint test p-value:	0.100	0.134	0.009	0.553	0.152
E: Black					
$Capacity_s \times \mathbb{1}[t=2022]$	-1.40	-1.12	-0.81	-1.90	-1.41
	(2.35)	(2.79)	(2.81)	(2.73)	(3.60)
$Capacity_s \times \mathbb{1}[t=2023]$	-1.26	-0.79	-0.22	-0.89	0.03
	(2.85)	(3.31)	(3.70)	(3.87)	(5.15)
Pretrends joint test p-value:	0.382	0.534	0.459	0.366	0.089
F: Total					
$Capacity_s \times \mathbb{1}[t=2022]$	3.25	3.29	2.54	1.64	-0.58
	(4.70)	(5.23)	(5.05)	(6.02)	(6.30)
$Capacity_s \times \mathbb{1}[t=2023]$	8.64	9.35	8.92	7.20	5.16
	(5.67)	(6.60)	(6.04)	(8.26)	(7.74)
Pretrends joint test p-value:	0.324	0.543	0.377	0.269	0.021
Avg. Number of Schools per Neighborhood:	23.7	13.1	12.4	5.4	4.5
Number of Neighborhoods:	29	51	57	166	181

Note: Table shows difference-in-differences estimates of enrollment across different neighborhood definitions. NTA stands for Neighborhood Tabulation Area. All specifications include school and zip code by year fixed effects. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

Table A5: Effects on Enrollment using Different Neighborhood Definitions, Binary Treatment

	(1) Sub-District	(2) Council District	(3) Community Board	(4) Zip Code	(5) NTA
A: English Language Learner					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	7.68	9.45*	8.38*	14.94**	10.75**
	(5.40)	(5.66)	(4.62)	(6.88)	(4.39)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	21.18**	21.74**	20.03***	25.37***	20.28**
	(8.80)	(8.80)	(7.15)	(9.32)	(8.01)
Pretrends joint test p-value:	0.860	0.264	0.210	0.217	0.387
B: Hispanic					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	5.54	5.57	9.12	11.25	-1.22
	(6.71)	(7.63)	(7.85)	(8.99)	(7.51)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	24.94**	25.00**	30.70***	29.99**	16.24*
	(9.69)	(11.91)	(9.79)	(12.27)	(9.10)
Pretrends joint test p-value:	0.739	0.772	0.884	0.620	0.626
C: White					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	4.78*	3.94	3.63	-0.75	4.07
	(2.78)	(3.09)	(2.84)	(3.69)	(4.02)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	3.83	3.57	2.61	-2.31	3.25
	(3.49)	(3.53)	(3.36)	(4.18)	(4.50)
Pretrends joint test p-value:	0.006	0.057	0.227	0.600	0.174
D: Asian					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	-2.00	0.85	-4.10*	3.57	-0.64
	(3.02)	(2.55)	(2.30)	(3.57)	(3.98)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	-4.10	-0.23	-6.10**	1.07	-3.45
	(3.00)	(2.99)	(2.77)	(4.83)	(4.40)
Pretrends joint test p-value:	0.156	0.110	0.041	0.219	0.058
E: Black					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	-2.12	-2.36	2.33	-1.89	4.24
	(4.90)	(6.11)	(5.84)	(5.86)	(6.39)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	0.71	-1.03	6.25	2.45	9.22
	(5.99)	(6.59)	(7.72)	(8.63)	(10.15)
Pretrends joint test p-value:	0.575	0.747	0.506	0.411	0.088
F: Total					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	5.24	7.31	10.68	11.74	6.29
	(9.49)	(11.08)	(10.27)	(14.02)	(12.29)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	22.74*	24.44	31.73**	28.96	22.99
	(13.24)	(15.67)	(13.44)	(19.20)	(16.47)
Pretrends joint test p-value:	0.577	0.460	0.383	0.448	0.033
Avg. Number of Schools per Neighborhood:	23.7	13.1	12.4	5.4	4.5
Number of Neighborhoods:	29	51	57	166	181

Note: Table shows difference-in-differences estimates of enrollment across different neighborhood definitions. NTA stands for Neighborhood Tabulation Area. All specifications include school and zip code by year fixed effects. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

A9 Controlling for Outmigration

Our main analysis addresses concerns about COVID-19 pandemic effects, which significantly impacted New York City, by including controls for linear trends and geographic proximity to account for varying pandemic impacts across schools with and without shelters. In our robustness checks, we further address these concerns by creating an additional control variable that measures out-migration in each city and school year using United States Postal Service (USPS) Change-Of-Address data.

We use the publicly available version, which covers December 2018 to June 2023, and provides monthly information on total in- and out-migration for individuals and families. We construct our variable by calculating net family migration (in-migration minus out-migration) at the city level. We then calculate totals for each academic year, adjusting for missing months when necessary. Due to the time limitations of the public dataset ending in June 2023, this variable is only available for the first post-period after the Buslift, so specifications including this variable don't provide estimates for the 2023/24 school year. We merge this variable with our main panel using the city the school is located in.

Table A6: Robustness Checks on Enrollment, Continuous Treatment

	(1)	(2)	(3)	(4)	(5)
A: English Language Learners					
$Capacity_s \times \mathbb{1}[t = 2022]$	5.46**	6.64**	7.65**	7.56**	7.18**
	(2.36)	(3.08)	(3.05)	(3.25)	(2.96)
$Capacity_s \times \mathbb{1}[t = 2023]$	11.08***	10.53**	11.15**	12.21***	
	(3.79)	(4.70)	(4.48)	(3.96)	
Pretrends joint test p-value:	0.663	0.166	0.185	0.234	0.145
B: Hispanics					
$Capacity_s \times \mathbb{1}[t = 2022]$	3.39	5.59	3.96	4.07	4.70
	(3.19)	(4.29)	(4.17)	(4.55)	(4.05)
$Capacity_s \times \mathbb{1}[t = 2023]$	11.19***	14.05**	11.54*	12.72**	
	(3.93)	(6.26)	(5.90)	(5.71)	
Pretrends joint test p-value:	0.200	0.253	0.352	0.388	0.234
C: White					
$Capacity_s \times \mathbb{1}[t = 2022]$	2.55*	-0.84	0.40	0.77	-0.48
	(1.42)	(1.74)	(1.93)	(1.94)	(1.92)
$Capacity_s \times \mathbb{1}[t = 2023]$	1.24	-2.85	-1.30	-0.67	
	(1.85)	(2.36)	(2.28)	(2.30)	
Pretrends joint test p-value:	0.033	0.230	0.144	0.234	0.305
D: Asian					
$Capacity_s \times \mathbb{1}[t = 2022]$	-1.01	-0.17	-0.85	0.74	-0.55
	(1.61)	(1.27)	(1.49)	(1.35)	(1.46)
$Capacity_s \times \mathbb{1}[t = 2023]$	-2.01	-1.73	-2.92	0.07	
	(1.69)	(2.04)	(2.24)	(1.97)	
Pretrends joint test p-value:	0.100	0.598	0.212	0.474	0.549
E: Black					
$Capacity_s \times \mathbb{1}[t = 2022]$	-1.40	0.35	-1.65	-1.90	-1.89
	(2.35)	(2.98)	(2.73)	(3.03)	(2.73)
$Capacity_s \times \mathbb{1}[t = 2023]$	-1.26	2.28	-0.57	-1.00	
	(2.85)	(4.36)	(3.94)	(4.29)	
Pretrends joint test p-value:	0.382	0.369	0.372	0.385	0.377
F: Total					
$Capacity_s \times \mathbb{1}[t = 2022]$	3.25	3.85	2.32	3.63	1.76
	(4.70)	(6.08)	(6.29)	(6.51)	(6.02)
$Capacity_s \times \mathbb{1}[t = 2023]$	8.64	10.30	7.05	10.72	
	(5.67)	(8.95)	(8.81)	(8.14)	
Pretrends joint test p-value:	0.324	0.348	0.212	0.319	0.277
N	3,672	3,480	2,106	3,354	2,891
# Schools	612	612	378	589	508
School FEs	x	x	x	x	x
Sub-district X Year FEs	x				
Zipcode X Year FEs		x	x	x	x
Linear Trends		x			
Schools w/ Shelters in 1 mile			x		
No HERRCs in 1 mile				x	
Control for Outmigration					x

Note: Table shows difference-in-differences estimates of enrollment across different student populations. Robustness checks include sub-district-by-year fixed effects, controls for linear trends, restricting the sample to schools within 1 mile of shelters, excluding schools near Humanitarian Emergency Relief and Rescue Centers (HERRCs), and controlling for out-migration. Note, data on outmigration is only available through 2022, so we are not able to estimate effects on the 2023 period when controlling for outmigration. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

Table A7: Robustness Checks on Enrollment, Binary Treatment

	(1)	(2)	(3)	(4)	(5)
A: English Language Learners					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	7.68	12.35*	15.35**	16.72**	14.94**
	(5.40)	(6.94)	(7.15)	(7.23)	(6.88)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	21.18**	21.74**	25.11**	28.92***	
	(8.80)	(9.65)	(9.91)	(8.89)	
Pretrends joint test p-value:	0.663	0.166	0.185	0.234	0.145
B: Hispanics					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	5.54	10.30	10.93	10.77	11.25
	(6.71)	(9.29)	(9.36)	(10.03)	(8.99)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	24.94**	28.66**	29.98**	30.77**	
	(9.69)	(12.97)	(12.98)	(12.67)	
Pretrends joint test p-value:	0.200	0.253	0.352	0.388	0.234
C: White					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	4.78*	-0.52	-0.16	1.35	-0.75
	(2.78)	(3.74)	(3.80)	(3.88)	(3.69)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	3.83	-1.98	-1.92	0.67	
	(3.49)	(4.43)	(4.28)	(4.11)	
Pretrends joint test p-value:	0.033	0.230	0.144	0.234	0.305
D: Asian					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	-2.00	5.26	2.94	5.00	3.57
	(3.02)	(3.65)	(3.67)	(3.88)	(3.57)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	-4.10	3.44	0.02	4.58	
	(3.00)	(4.86)	(4.96)	(4.98)	
Pretrends joint test p-value:	0.100	0.598	0.212	0.474	0.549
E: Black					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	-2.12	1.16	-1.20	-3.08	-1.89
	(4.90)	(5.90)	(5.93)	(6.37)	(5.86)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	0.71	6.72	3.50	1.33	
	(5.99)	(8.76)	(8.85)	(9.54)	
Pretrends joint test p-value:	0.382	0.369	0.372	0.385	0.377
F: Total					
$Hi\ Capacity_s \times \mathbb{1}[t = 2022]$	5.24	14.48	13.02	13.27	11.74
	(9.49)	(14.35)	(14.52)	(15.39)	(14.02)
$Hi\ Capacity_s \times \mathbb{1}[t = 2023]$	22.74*	32.80*	30.33	34.52*	
	(13.24)	(19.88)	(20.11)	(20.16)	
Pretrends joint test p-value:	0.324	0.348	0.212	0.319	0.277
N	3,672	3,480	2,106	3,354	2,891
# Schools	612	612	378	589	508
School FEs	x	x	x	x	x
Sub-district X Year FEs	x				
Zipcode X Year FEs		x	x	x	x
Linear Trends		x			
Schools w/ Shelters in 1 mile			x		
No HERRCs in 1 mile				x	
Control for Outmigration					x

Note: Table shows difference-in-differences estimates of enrollment across different student populations. Robustness checks include sub-district-by-year fixed effects, controls for linear trends, restricting the sample to schools within 1 mile of shelters, excluding schools near Humanitarian Emergency Relief and Rescue Centers (HERRCs), and controlling for out-migration. Note, data on outmigration is only available through 2022, so we are not able to estimate effects on the 2023 period when controlling for outmigration. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.

A10 Evidence from Parent and Teacher Surveys

Table A8: Effects on Parent and Teacher Survey Responses

	(1) Total Response	(2) Inclusive Leadership	(3) Outreach	(4) Involvement Influence	(5) Principal Trust	(6) Teacher Trust
A: Parent Survey, School Environment						
$Capacity_s \times \mathbb{1}[t=2023]$	-20.917**	-0.006	-0.007***	-0.006	-0.005	-0.006**
	(8.114)	(0.004)	(0.002)	(0.006)	(0.004)	(0.002)
$Capacity_s \times \mathbb{1}[t=2024]$	-12.375	-0.001	-0.000	-0.002	-0.004	0.001
	(9.403)	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)
Mean Y	276.048	0.943	0.944	0.925	0.945	0.956
N	3,600	3,594	3,600	3,594	3,600	3,600
# Schools	600	599	600	599	600	600
Pretrends joint test p-value:	0.410	0.263	0.047	0.200	0.118	0.249
B: Teacher Survey, School Environment						
$Capacity_s \times \mathbb{1}[t=2023]$	-0.969	0.005	-0.004	0.021	0.009	0.004
	(0.813)	(0.010)	(0.004)	(0.014)	(0.011)	(0.011)
$Capacity_s \times \mathbb{1}[t=2024]$	-0.127	0.001	-0.002	0.017	-0.005	0.002
	(0.581)	(0.011)	(0.004)	(0.014)	(0.018)	(0.010)
Mean Y	37.256	0.882	0.969	0.687	0.836	0.875
N	3,258	3,252	3,252	3,252	3,252	3,252
# Schools	543	542	542	542	542	542
Pretrends joint test p-value:	0.752	0.204	0.909	0.005	0.096	0.577

	(1) Quality Discussion	(2) Cultural Awareness	(3) Peer Collaboration	(4) Classroom Behavior	(5) Program Coherence	(6) Safety
C: Teacher Survey, Classroom/Curriculum Questions						
$Capacity_s \times \mathbb{1}[t=2023]$	0.003	0.003	-0.000	-0.000	0.004	0.004
	(0.012)	(0.005)	(0.011)	(0.012)	(0.013)	(0.010)
$Capacity_s \times \mathbb{1}[t=2024]$	-0.001	0.002	0.000	-0.002	0.004	-0.002
	(0.016)	(0.005)	(0.014)	(0.015)	(0.013)	(0.008)
Mean Y	0.712	0.943	0.884	0.753	0.840	0.901
N	3,240	3,258	3,252	3,240	3,246	3,234
# Schools	540	543	542	540	541	539
Pretrends joint test p-value:	0.332	0.562	0.609	0.766	0.120	0.819

Note: Tables show difference-in-differences estimates on responses from parent and teacher surveys. All specifications include school fixed effects and zip code by year fixed effects. *, **, *** correspond to 10, 5, and 1% significance levels, respectively. Standard errors are clustered at the school level.