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Unexpected Arrivals: The Spillover Effects of Mid-Year Entry on Stable Student Achievement in New York City

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Across the country and in urban areas in particular, many students change schools during the academic year. While much research documents the impact of changing schools on the academic achievement of mobile students themselves, less research explores whether new arrivals have negative spillovers on stable classmates. The lack of research on impacts of mid-year entry is problematic, as poor, minority, and low-achieving students are disproportionately exposed to mid-year entry. In this study, we use a rigorous causal identification strategy and rich longitudinal data on fourth- through eighth-grade students in the New York City (NYC) public schools to estimate the impact of exposure to mid-year entry on the achievement of stable students. We analyze heterogeneous effects of mid-year entrants by origin (arriving from other NYC public schools, from other U.S. school systems, or from other countries), determine the extent to which mid-year entrants' characteristics mediate the impact of mid-year entry, and explore the moderating influence of stable students' characteristics. We find small negative effects of mid-year entry on both math and English language arts test scores in the short run. These impacts are not driven by mid-year entrant characteristics and are somewhat larger for Asian students and those who do not qualify for free or reduced-price lunch. Finally, results suggest mid-year entry continues to negatively influence the math performance of stable students beyond the year of exposure. We discuss the relevance of results and conclude with recommendations for future research.

Keywords: *student mobility, mid-year entry, spillover effects, peer effects*

Introduction

Among the considerable challenges faced by urban school districts in the United States, the arrival of students after the beginning of the school year is particularly troublesome. Student entry and exit during the year is so prevalent in Washington, D.C., for example, an official from the Office of the State Superintendent of Education remarked, "This almost looks like our admissions are rolling" (Brown, 2013). In the D.C. Public Schools, 8.3% of students in the spring of 2012 had arrived after September (Jones, 2013), while the Chicago Public Schools experienced a similarly high late entry rate of 7.1% in 2007 (de la Torre & Gwynne, 2009). These unexpected arrivals pose an administrative burden for school staff, create both management and pedagogical challenges for teachers, and ultimately can harm the academic performance of stable peers.

Much research has documented the negative impact of changing schools on the academic achievement of mobile students themselves,[1] but little attention has been devoted to the negative repercussions this mid-year mobility has for stable students. Mid-year entrants (MYEs) may negatively affect the achievement of their classmates through two key potential mechanisms. First, MYEs may disrupt the learning environment, as teachers interrupt instruction to acclimate new students to classroom policies and procedures (Lash & Kirkpatrick, 1990). Such disruption may also draw resources away from stable students if teachers disproportionately allocate time to helping new students catch up (Lazear, 2001). Second, MYEs may alter the composition of classrooms, and these changes in peer characteristics may influence stable students' outcomes.

This study explores new dimensions of the spillover effects of mid-year entry; specifically, we answer the following five questions:

Research Question 1: What is the impact of mid-year entry on stable student achievement?

We use rich data from New York City (NYC) to estimate the causal effect of exposure to new students on stable students' math and English language arts (ELA) achievement in elementary and middle school grades. Our research design, which includes a set of two-way fixed effects, is more rigorous than most prior studies.

Research Question 2: Do effects depend on the origin of MYEs?

Next, we distinguish between MYEs who transfer from other schools in the same district and those who enter from other school systems. Specifically, we estimate the impact of MYEs by origin: those transferring from other NYC public schools, those arriving from other U.S. school systems, and those entering from other countries. It is important to estimate separate effects by MYE origin as these groups of new students may affect stable students' achievement differently. For example, students moving between schools in the same district may be the least disruptive, as there is likely to be greater alignment of academic curricula and school policies across schools within the same district. Students entering from another U.S. public school district or a private/parochial school may be more disruptive than intra-district movers, as they likely have less continuity in instruction. Finally, MYEs from other countries may be helpful or harmful for stable student achievement. On one hand, recent immigrants face particularly dramatic changes when they arrive in schools mid-year, having to adjust to a new country, entirely different peer groups, and often a second language. On the other hand, recent immigrants are likely to be a positively selected group (e.g., with motivated parents) and thus may positively influence peer achievement.

Research Question 3: Is the impact of mid-year entry mediated by characteristics of the entrants?

We next explore whether the effect of mid-year entry is mediated by the characteristics of the new entrants; specifically, we determine if the impact of mid-year entry is attenuated after including the demographic characteristics and prior achievement of new students in our models. This is an important contribution, as research has established that peer characteristics influence students' academic outcomes; the implication for this study is that MYEs may influence student test scores not just by disrupting the classroom environment but also by changing the demographic and educational composition of stable students' peer groups. Previous studies have not specifically addressed this question.

Research Question 4: Is the impact of mid-year entry moderated by stable student characteristics?

Drawing on a large data set with substantial numbers of students across many subgroups, we are able to determine whether and to what extent the characteristics of stable students moderate the effect of new students entering mid-year. Previous studies have been limited in their ability to estimate subgroup effects due to relatively small or homogeneous samples.

Research Question 5: Does the impact of mid-year entry persist beyond the year of exposure?

Finally, we estimate the impact of contemporaneous and prior exposure to mid-year entry to provide descriptive evidence of how exposure to mid-year entry may influence student achievement over time. Little prior research has explored whether the impact of exposure to in-mobility persists beyond 1 year.

We are able to answer these five important research questions by using rich panel data on public school students in NYC, following them across more grades and more years than previous studies. Specifically, our large and diverse sample includes fourth- through eighth-grade students in traditional public schools in NYC from 2005 to 2008. NYC is an appealing context for this research, as findings may be relevant for other large urban public school districts. The composition of the NYC public schools is in many respects similar to other urban school districts, and as the largest school district in the United States, NYC has greater numbers of students in typically underrepresented groups, allowing us to explore outcomes for more student subgroups than is possible elsewhere. Furthermore, while NYC has many unique neighborhoods (e.g., Times Square, Financial District), much of the city is more similar to other urban areas in the United States (e.g., the boroughs of Queens and Staten Island).

The spillover effect of mid-year entry on stable students' achievement—and how the impact depends on the demographic characteristics of newly entering and stable students—has important implications for education policy. In particular, mid-year entry may exacerbate inequalities across schools. Prior research finds that mobility rates tend to be higher in schools with greater concentrations of retained and minority students (Rumberger, 2003; Rumberger & Thomas, 2000); specifically in NYC, we show that poor, minority, and low-achieving students are disproportionately exposed to high mid-year entry. If policymakers and practitioners ignore mid-year entry as an important contributor to student outcomes, they may fail to identify students who could potentially benefit from additional support. In the conclusion, we suggest avenues for future research that may help inform district and school approaches to mitigating the spillover effects of mid-year mobility.

Prior Research

Few studies estimate the spillover effects of mobility, per se, and only three studies estimate the effects of entry, or in-mobility. Gibbons and Telhaj (2011) use data on British elementary students to estimate long changes in performance due to mobility from the equivalent of fourth to seventh grade (ages 7 to 11), finding small but statistically significant negative effects. Gibbons and Telhaj do not specifically address mid-year entry, but rather measure in-mobility as the average annual rate of entry to the cohort (whether during or between academic years) over the 4 years. In addition, they include only school and year effects in their models and are not able to control for unobserved heterogeneity among stable classmates.

More closely related to our research, two previous studies estimate the impact of mid-year arrivals on the achievement of stable peers. Hanushek, Kain, and Rivkin (2004) use data on all Texas students in three grades (3–5 or 4–6) to estimate the impact of mid-year entry on gains in math performance. Using a series of individual, school-by-grade, and school-by-year effects in their models, they find new student entry has small negative effects. Their study is limited, however, as it includes only 3 years of student data and not explore whether impacts persist over time. Raudenbush, Jean, and Art (2011) explore mid-year mobility in the Chicago Public Schools and base their estimation on students between the ages of 8 and 10 over two different 3-year periods. They use forms of propensity score matching or inverse probability weighting with school and year or grade and year effects, finding that new students are most harmful for low-scoring African American children and do not significantly affect White or Hispanic students. As in Hanushek et al. (2004), only 3 years of data for elementary school students are included in the analysis, and subgroup models are somewhat limited by the relative lack of diversity in the sample (compared with NYC public schools).

Prior research on peer effects is relevant to the mechanisms through which MYEs may affect stable student achievement. Research on disruptive peers finds that classmates with behavior problems have negative spillovers on the behavior and achievement of their classmates. For example, students are more likely to misbehave themselves and have lower test scores when their classmates have been exposed to domestic violence at home (Carrell & Hoekstra, 2010) or have discipline problems (Figlio, 2007). In addition, exposure to frequently absent students (Gottfried, 2011) and retained students (Gottfried, 2013b, 2013c), who may disrupt class or draw resources from stable students, negatively influences student outcomes.

Turning to the gender, race, and achievement of peers, an extensive literature finds that student outcomes are influenced by their classmates' demographics and performance levels. For example, several studies find that female students have a positive impact on their classmates' test scores (Hoxby, 2000; Hu, 2015; Lavy & Schlosser, 2011), and there is evidence that minority peers can impede academic achievement (e.g., Cooley, 2006; Hanushek, Kain, & Rivkin, 2002; Hoxby, 2000). Many studies report that higher achieving peers positively influence student achievement, both in K–12 and higher education (e.g., Burke & Sass, 2013; Cooley, 2006; Hanushek, Kain, Markman, & Rivkin, 2003; Hoxby & Weingarth, 2005; Sacerdote, 2001; Vigdor & Nechyba, 2007; Zimmerman, 2003).

Finally, the methods used in studies of peer effects inform our empirical approach, which identifies impacts by isolating "random shocks" of peers with various characteristics using combinations of school, grade, and year fixed effects.[2] The logic of the identification strategy is that after removing the systematic effects of school-grades, school-years, and grade-years, what remains is idiosyncratic variation in students' exposure to peers with different characteristics—or in our case, peers who are new students. Thus, we use random variation in students' exposure to peers who enter mid-year over time to estimate the impact of mid-year entry on the performance of stable students.

Data

Data Sources

We use two key data sources in this study: detailed student-level administrative data from the NYC Department of Education and school-level data from the New York State Education Department's School Report Cards (SRCs). Student-level data include information on gender, race/ethnicity, nativity, poverty (eligibility for free or reduced-price lunch or attendance in a universal free meal school), limited English proficiency (LEP), eligibility for special education (SPED), and performance on standardized math and ELA exams administered statewide in grades 3 through 8.[3] Importantly, students have unique identifiers, allowing us to follow them across grades and schools during their tenure in NYC public schools. Critical to our analyses, each student record also includes codes identifying the school attended at three points during the academic year: October, March, and June.

School-level data from the SRCs provide average student characteristics, including the percentage of students who are Black, Hispanic, Asian, or White, eligible for free or reduced-price lunch, and LEP. The SRCs also include average teacher characteristics, such as the percentage with a master's degree or higher and the percentage with fewer than 3 years of experience in the school. Finally, we use enrollment numbers by grade from the SRCs to identify school types (e.g., elementary, middle) and to measure school size (log of total student enrollment).

Measures

We use school codes at three points in the academic year to identify stable students and movers. A stable student attends the same school for the entire academic year (October, March, and June). An MYE arrives in a school after October, whether from another NYC public school, from the private/parochial sector, or from another school district or country entirely.[4] A mid-year exiter (MYX) leaves a school during the school year, and a summer entrant is new to a school in October. Our key independent variable is the mid-year entry ratio, which is calculated by dividing the number of students who enter grade g in school s in year t mid-year by the total number of students attending grade g in school s as of October 31 in year t.[5] We also decompose the MYE rate into three separate ratios by origin: the ratio of MYEs from other NYC public schools, the ratio of MYEs from other U.S. districts or private schools, and the ratio of MYEs from other countries.

Note that we measure mid-year entry at the grade level. While school-level mid-year entry could influence student achievement (e.g., by drawing on schoolwide resources, such as school counselors), it is less salient to individual students than grade-level mid-year entry. Classroom-level measures are problematic for two reasons. First, classroom-level mid-year entry is more likely to be endogenous than grade-level mid-year entry because arriving students may be strategically assigned to specific teachers. Second, students in middle schools, who make up some of our sample, may take classes with different groups of students throughout the day, and this phenomenon is unobserved in the data.[6]

In addition to these MYE ratios, we construct two other grade-level mobility measures, whose effects on stable students (and whose influence on estimated coefficients of the impact of mid-year entry) we analyze in robustness tests. First, the MYX ratio is calculated by dividing the number of MYXs by the number of students enrolled in October. Second, the summer entry ratio is constructed by dividing the number of students who are new to a school at the beginning of the school year by the number of students enrolled in October.

Sample

We merge the student-level and school-level data to create a longitudinal data set of all fourth- through eighth-grade students attending traditional public schools in NYC between 2005 and 2008.[7] Our main analytic sample includes stable students observed for 3 or 4 years. This analytic sample includes more than 800,000 student-year observations, with more than 250,000 unique students attending more than 1,000 different schools. In a robustness test, we use the full sample of all fourth- through eighth-grade students attending NYC public schools in this time period, more than 1.3 million observations over the 4-year period.

Using the full sample, Table 1 presents characteristics of stable students and MYEs in 2008.[8] While most students are stable, nearly 11,000 are MYEs. Compared with stable students (column 1), MYEs (column 2) are more likely to be Black (38.1% vs. 30.4%) or to qualify for free lunch (80.2% vs. 73.8%) and less likely to be White (8.1% vs. 14.5%) or Asian (12.7% vs. 15.4%). MYEs are also much more likely to be foreign-born (29.1% vs. 16.8%), recent immigrant (17.6% vs. 5.5%), and LEP (21.2% vs. 9.9%). MYEs are more likely than stable students to live in the Bronx, a northern section of NYC (27.1% vs. 22.0%), and are less likely to live in Queens, an eastern area of NYC (24.9% vs. 28.3%). There are small differences across the grade distribution, with MYEs somewhat less likely to be eighth graders (17.8% vs. 20.6%) and more likely to be fourth graders (22.3% vs. 19.8%). Finally, MYEs are less likely to take the math exam (86.9% vs. 99.2%) and much less likely to take the ELA exam (63.5% vs. 98.0%) than stable students; when MYEs do take standardized tests, they perform approximately half a standard deviation worse (−0.685 vs. 0.023 for math, −0.444 vs. 0.012 for ELA).

Columns 3 through 5 show characteristics of MYEs by origin. In 2008, approximately 75% of MYEs arrived from other NYC public schools, with the remaining 25% of MYEs split nearly evenly between those arriving from other U.S. districts and from other countries. Because the vast majority of MYEs arrive from other NYC schools, this subsample closely resembles MYEs overall. There are, however, considerable differences in the characteristics of MYEs by origin. MYEs from outside the district (and especially those arriving from other countries) are much more likely to be Asian, foreign-born, recent immigrant, and LEP—and less likely to be Black or to participate in special education—than those transferring within the district. MYEs from outside the district are much less likely to take the ELA exam than MYEs transferring from other NYC public schools, and compared with the intra-district movers, MYEs from other U.S. school systems perform better, whereas MYEs from other countries perform worse. Finally, MYEs from outside the district are more likely to take the math exam and perform considerably worse on the test than MYEs from other NYC public schools.

The Nature of the Problem: A Statistical Portrait of Mid-Year Entry in NYC

While mid-year entry is not a major issue for most students in the NYC public schools, a significant number of stable students are exposed to

TABLE 1

Characteristics of Students by Types of Moves, Grades 4 to 8, 2008

		Mid-year entrants			
	Stable (1)	Overall (2)	NYC (3)	United States (4)	Other country (5)
% who are					
Female	50.4	48.4	48.1	49.2	49.0
Asian	15.4	12.7	8.2	17.5	34.3
Black	30.4	38.1	42.5	28.3	21.2
Hispanic	39.6	41.0	41.8	42.7	35.0
White	14.5	8.1	7.5	10.8	9.1
Free lunch	73.8	80.2	80.8	73.4	81.9
Reduced-price lunch	8.3	4.6	4.8	3.1	4.6
Foreign born	16.8	29.1	14.8	43.3	98.3
Recent immigrant	5.5	17.6	5.5	0.0	100.0
Special education	11.5	14.3	18.5	1.6	0.3
Limited English proficient	9.9	21.2	10.7	37.0	67.7
% who live in					
Manhattan	11.9	11.4	11.1	14.1	10.9
Bronx	22.0	27.1	29.0	26.4	18.7
Brooklyn	31.6	32.2	32.4	30.6	32.3
Queens	28.3	24.9	22.7	25.8	34.5
Staten Island	6.2	4.4	4.8	3.2	3.7
% in					
Grade 4	19.8	22.3	23.1	22.0	18.1
Grade 5	19.7	19.4	19.5	18.9	19.2
Grade 6	19.6	20.0	19.9	20.3	20.8
Grade 7	20.3	20.5	20.5	20.7	20.1
Grade 8	20.6	17.8	17.1	18.1	21.7
Standardized tests					
% taking math	99.2	86.9	85.0	89.3	95.9
% taking ELA	98.0	63.5	76.1	27.0	21.8
Math z-score	0.023	−0.685	−0.598	−0.916	−0.950
ELA z-score	0.012	−0.444	−0.437	−0.196	−0.816
Total students	319,223	10,759	8,146	1,163	1,450

Note. Stable students attend the same school for the entire year (October, March, and June). MYEs (in columns 2-5) arrive in a school after October. MYEs are categorized by origin: other NYC schools (column 3), other U.S. districts (column 4), and other countries (column 5). ELA = English language arts; MYE = Mid-year entrant; NYC = New York City.

considerable mid-year entry. To illustrate, Figure 1 shows the distribution of MYE ratios experienced by stable students in 2008. At the mean, the MYE ratio is 0.033, indicating that the average student is in a grade with three to four MYEs for every 100 students enrolled in October. Over 10% of students are not exposed to any MYEs, and at the 25th percentile of school-grade mid-year entry, the MYE ratio is just 0.014. At the top of the distribution, however, students are exposed to very high rates of new student entry. At the 90th percentile, the MYE ratio is 0.067, and at the 95th percentile, the MYE ratio is 0.083.

To understand the practical implications of these numbers, suppose a typical grade has 100 students across four classrooms.[9] On average, there are 3 to 4 total new students entering mid-year per grade (nearly one per class), but at the

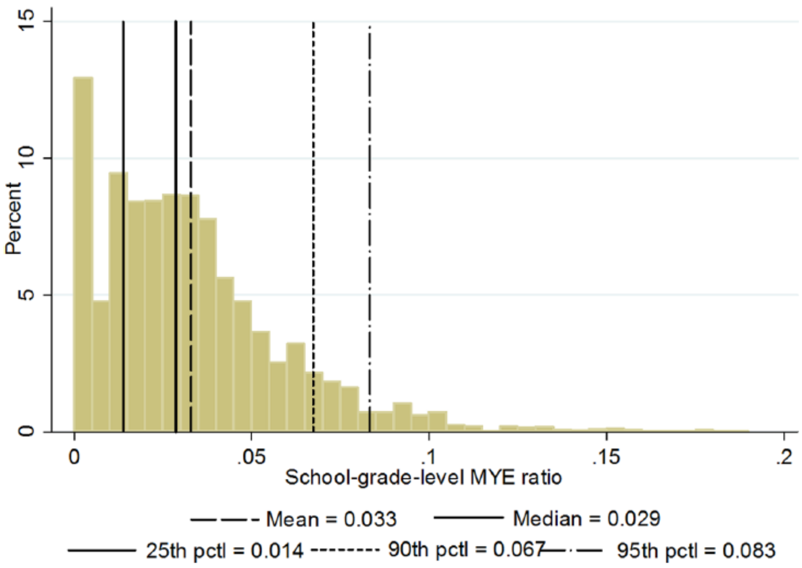

FIGURE 1. *Distribution of MYE ratios experienced by students in grades 4-8, 2008.*
Note. MYE ratios at the 5th and 10th percentiles are 0.000. Width of bars is 0.005. MYE = mid-year entrant.

high end of the distribution, there are between 8 and 9 of these entrants (more than two per class). Because NYC is such a large district, even 5% of students is a meaningfully large group. In 2008, for example, 16,186 fourth- through eighth-grade stable students in 131 schools experienced MYE ratios at or above 0.083.

The considerable variation in student exposure to new entrants may raise concern that students in high-mobility schools (grades) are different than students in low-mobility schools (grades). To explore this issue, in Table 2 we present the characteristics of students who experience very low and very high mid-year entry in 2008. We include the characteristics of students exposed to no mid-year entry and those in the bottom and top deciles of non-zero mid-year entry.[10] Students exposed to no mid-year entry and to low mid-year entry are observably similar, so for simplicity we describe differences between students with low and high exposure.

First, note that mobility rates are related. On average, students in the bottom decile of exposure to new students experience a MYE ratio of 0.008 and also relatively low rates of mid-year exit (MYX = 0.021) and summer entry (0.177). Students in the top decile of exposure to new students, however, experience an average MYE ratio of 0.094, an average MYX ratio of 0.059, and an average summer entry ratio of 0.342.[11] These relationships indicate that school grades with higher mid-year entry have greater overall school churn; in a robustness test, we control for multiple measures of student mobility to ensure our estimated effects reflect the unique impact of mid-year entry and not the broader effect of school instability.

Students who experience high mid-year entry are much more likely to be Black (50.6% vs. 23.4%), Hispanic (39.8% vs. 30.2%), eligible for free or reduced-price lunch (90.1% vs. 67.9%), LEP (11.8% vs. 5.7%), and recent immigrant (6.6% vs. 3.7%) than students exposed to low mid-year entry. Students in high-mobility grades are much less likely to be Asian (6.3% vs. 18.0%) or White (3.3% vs. 28.4%) than those in low-mobility grades and also have lower prior performance on standardized math (−0.310 vs. 0.324) and ELA exams (−0.277 vs. 0.333). Although students experiencing no new arrivals mid-year are distributed nearly evenly across grades, there are discrepancies between students in low- and high-mobility grades. Students exposed to high MYE ratios are more likely to be in fourth or sixth grade and less likely to be in eighth grade.

TABLE 2

Characteristics of Stable Students in Low- and High-Mobility School-Grades, Grades 4 to 8, 2008

		Non-zero MYE ratio	
	No MYEs	Low MYE ratio	High MYE ratio
	(1)	(2)	(3)
MYE ratio criteria	ratio = 0	0 < ratio ≤ 0.011	ratio ≥ 0.070
Mean MYE ratio	0.000	0.008	0.094
Mean MYX ratio	0.019	0.021	0.059
Mean summer entry ratio	0.204	0.177	0.342
Student characteristics			
Female	52.5%	51.3%	49.7%
Asian	14.0%	18.0%	6.3%
Black	29.2%	23.4%	50.6%
Hispanic	33.2%	30.2%	39.8%
White	23.6%	28.4%	3.3%
Free or reduced-price lunch	71.1%	67.9%	90.1%
Foreign born	11.5%	14.3%	15.8%
Recent immigrant	2.4%	3.7%	6.6%
Limited English proficient	4.8%	5.7%	11.8%
Special education	11.0%	10.1%	12.5%
Lagged z-math	0.323	0.324	−0.310
Lagged z-read	0.351	0.333	−0.277
Grade			
4	17.5%	16.0%	27.4%
5	20.1%	16.6%	15.5%
6	20.6%	17.7%	24.7%
7	20.5%	21.7%	20.9%
8	21.2%	28.0%	11.4%
School characteristics			
% of teachers with < 3 years experience	34.6%	38.0%	30.3%
% of teachers with master's or higher	17.6%	15.2%	19.3%
Elementary	29.0%	30.3%	33.6%
Elementary–middle	27.8%	13.0%	14.9%
Middle	29.3%	53.0%	49.6%
Middle–high	10.3%	3.8%	1.7%
Total enrollment	660	968	634
Total students	37,500	26,300	28,513
% of all students	11.7%	10%	10%

Note. The sample does not include students who are MYEs. Elementary schools have a high grade of 4, 5, or 6. Elementary–middle schools have a low grade of 4 or lower and a high grade of 7 or 8. Middle schools have only grades 5, 6, 7, and 8. Middle–high schools have a high grade of 9, 10, 11, or 12. MYE = mid-year entrant; MYX = mid-year exiter.

In terms of school characteristics, perhaps counterintuitively, students exposed to high mid-year entry attend schools with more experienced teachers than students exposed to low mid-year entry, measured both by the percentage of teachers with fewer than 3 years of experience at the school (30.3% vs. 38.0%) and the percentage of teachers with a master's degree or higher (19.3% vs. 15.2%). Students experiencing high mid-year entry are somewhat more likely to attend elementary schools rather than middle or middle–high schools. Finally, students exposed to low mid-year entry attend much larger schools on average (968 students) than students with zero exposure (660 students) or high exposure (634 students).

These analyses indicate there are considerable numbers of students who experience high mid-year entry, and exposure to new students varies widely. Importantly, minority, poor, LEP, recent immigrant, and lower performing students more likely to experience high mid-year entry.

Identifying the Effect of Mid-Year Entry on Stable Students' Achievement

Estimating Short-Run Effects

The key challenge in estimating the impact of MYEs on the achievement of stable students is that mid-year entry is not random and, in particular, may be associated with student, school, grade, and year characteristics that influence academic outcomes. For example, as previously described, students exposed to high mid-year entry are disproportionately disadvantaged. In addition, MYE rates may be correlated with changes at the school-grade level (such as a curricular reform in a key grade for some schools), at the school-year level (such as a new principal), or at the grade-year level (such as a districtwide choice of a new textbook in a given year). Thus, simple models relating mid-year entry to stable student outcomes may conflate MYE ratios with grade, year, school, and student characteristics, thereby overstating the negative effect of these new students. The challenge is to distinguish between the impact of mid-year entry and the influence of other student and environmental factors that contribute to student test scores.

To address this challenge empirically, we estimate models controlling for the characteristics of schools, grades, years, and stable students by including observed student demographic and education variables and three pairs of two-way fixed effects: school-by-grade, school-by-year, and grade-by-year. We address the possibility that unobserved stable student characteristics, such as motivation and parental resources, are related to exposure to both mid-year entry and test scores in two ways. First, we estimate student fixed effects models, which control for time-invariant, unobserved student characteristics, comparing students with themselves over time. Second, we estimate value-added models (VAMs), which control for students' lagged test scores. In the VAM specifications, prior test scores are intended to reflect many unobserved student characteristics, distilling multiple dimensions of student ability and experiences into one overall prior achievement measure.[12]

Specifically, to analyze the impact of exposure to mid-year entry on the achievement of stable students in the short run (in the same academic year), we estimate the following model:

$$\begin{aligned}\text{Test}_{igst} &= \beta_0 + \beta_1 MYE_{gst} + \mathbf{X}'_{igst}\beta_2 + \mathbf{S}'_{st}\beta_3 \\ &\quad + \gamma_{sg} + \delta_{st} + \alpha_{gt} + \tau_i + \varepsilon_{igst},\end{aligned} \tag{1}$$

where Test_{igst} is the performance on the math or ELA exam of stable student i in grade g in school s in year t; MYE_{gst} is the mid-year entry ratio; $\mathbf{X}'_{igst}$ is a vector of stable student characteristics that change over time, including eligibility for free or reduced-price lunch, recent immigrant status, LEP, and SPED; and $\mathbf{S}'_{st}$ is a vector of time-varying school characteristics, including average student characteristics (the percentage of students who are Black, Hispanic, Asian, free lunch, reduced-price lunch, and LEP), average teacher characteristics (the percentage of teachers with master's degrees and the percentage with fewer than 3 years of experience at the school), and the natural log of total school enrollment. We also include indicators for having any MYEs and for magnet-type schools, which have restricted mid-year entry.[13]

The model includes school-by-grade (γ_{sg}), school-by-year (δ_{st}), and grade-by-year (α_{gt}) fixed effects as well as a student effect (τ_i). This set of fixed effects is designed to identify variation in mid-year entry ratios around the school-grade, grade-year, and school-year means and relies on within-student variation in exposure to mid-year entry. That is, estimates are identified by small changes in student exposure to new students across schools and grades over time. After including the comprehensive set of two-way fixed effects, it is unlikely that estimates are biased by factors that could be correlated with both mid-year entry and student outcomes.[14]

A critical assumption underlying this approach is that the two-way fixed effects allow us to capture random variation in student exposure to new students that is uncorrelated with stable student characteristics. Although it cannot be tested directly, we explore the validity of this assumption by examining whether observed student characteristics predict mid-year entry at the school-grade level with and without the two-way fixed effects. Results of this balancing test support our identification strategy. (See the technical appendix for further explanation and results.)

Further Analyses: Heterogeneity, Mediation, Moderation, and Persistence

We augment the basic short-term model to answer more nuanced research questions. To explore heterogeneous effects by MYE origin (Research Question 2), we substitute the three origin-based MYE ratios (MYEs from other NYC public schools, from other U.S. school systems, and from other countries) for the overall MYE ratio. Note that because MYEs from outside NYC are often limited English proficient and rarely take the ELA exam (see Table 1), it is likely that these students have different ELA learning environments than stable students, with less opportunity to influence stable student ELA performance. For example, they may be "pulled out" for separate language instruction. We therefore do not show the coefficients for the impact of MYEs from outside the NYC public schools on the ELA achievement of stable peers.

To determine whether the impact of mid-year entry is mediated by the characteristics of MYEs (Research Question 3), we control for the shares of MYEs who are Black, Hispanic, Asian, poor, LEP, SPED, foreign-born, and recent immigrant as well as the average prior math and ELA test scores of these new students. After controlling for the characteristics of MYEs (changes in observed peer quality), point estimates can be thought of as capturing the disruptive effect of MYEs.[15]

To explore whether the characteristics of stable students moderate the impact of mid-year entry (Research Question 4), we estimate the impact of mid-year entry on achievement for subgroups of stable students (by race, gender, and poverty status).[16]

Finally, to explore whether the impact of exposure to mid-year entry persists beyond the current year (Research Question 5), we simultaneously estimate the impact of prior and contemporaneous exposure to mid-year entry. Specifically, we augment our main model by including a measure of exposure to mid-year entry in the previous academic year. With this model, we are able to determine whether exposure to mid-year entry in the prior year continues to influence academic achievement, above and beyond any potential impact of mid-year entry in the current year.

Results

Short-Term Impact of Exposure to Mid-Year Entry

Our main results are estimated using the sample of students observed in Grades 4 through 8 for 3 or 4 years (2005–2008); that is, we exclude students observed for only 1 or 2 years.[17] Results from the base specification for estimating short-term effects (Model 1) are shown in Table 3. For both math (columns 1–2) and ELA (columns 3–4), we estimate small, negative effects of exposure to mid-year entry. For math, the estimated coefficients in the student fixed effects (−0.28) and value-added specifications (−0.22) are quite similar. We estimate slightly smaller effects in the ELA models, with coefficients of −0.19 in the student fixed effects specification (column 3) and −0.06 in the VAM (column 4). Moving forward, we present results from student fixed effects models, which we believe more effectively control for unobserved student-level heterogeneity than the VAMs.[18]

Using point estimates from the student fixed effects models to interpret these results, the approximately −0.20 to −0.30 estimated coefficients indicate that an increase of 0.05 in the MYE ratio, equivalent to the difference between the mean (0.033) and the 95th percentile (0.083) of exposure in 2008, would reduce stable students' achievement by approximately 0.01 to 0.02 *SD*s.[19] These are small but meaningful effects, especially in a district as large as NYC, where even the 95th percentile represents a meaningfully large group of students (over 4 years, 5% of our analytic sample represents nearly 32,000 students).

TABLE 3

Regression Results: Estimates of the Impact of Mid-Year Entry on Stable Student Achievement Grades 4 to 8, 2005 to 2008

	Math		ELA	
	Student FE	VAM	Student FE	VAM
	(1)	(2)	(3)	(4)
MYE ratio	−0.28*** (0.04)	−0.22*** (0.03)	−0.19*** (0.04)	−0.06** (0.03)
Own characteristics	Y	Y	Y	Y
School characteristics	Y	Y	Y	Y
School-grade FE	Y	Y	Y	Y
Grade-year FE	Y	Y	Y	Y
School-year FE	Y	Y	Y	Y
Student FE	Y	N	Y	N
Observations	843,172	843,172	814,807	814,807
R^2	0.55	0.62	0.45	0.55

Note. Sample includes students who are observed in grades 4 to 8 for 3 or 4 years between 2005 and 2008. Own characteristics include free and reduced-price lunch eligibility, recent immigrant status, LEP, and SPED. Time-varying school characteristics include the percentages of students who are Black, Hispanic, Asian, free lunch, reduced-price lunch, and LEP; the percentages of teachers with master's degrees and fewer than 3 years of experience; and the natural log of total school enrollment. Indicators are included to control for school grades with any MYEs and for schools that ever have no MYEs (magnet-type schools). The dependent variable is a student's test score measured as a *z*-score. Constant not shown. Standard errors in parentheses. ELA = English language arts; FE = fixed effects; LEP = limited English proficiency; MYE = mid-year entrant; SPED = special education; VAM = value-added model.
$^*p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

Impact by MYE Origin

Results shown in Table 4 address the second research question, whether there are heterogeneous effects depending on whether MYEs are coming from other NYC public schools, other U.S. school systems, or other countries. For both math (−0.25, column 2) and ELA (−0.18, column 6), the estimated effect of MYEs from other NYC public schools is quite similar to the estimated effect of the overall MYE ratio. This is unsurprising, as the vast majority of MYEs are arriving from other NYC public schools (Table 1). As described previously, due to likely differences in how MYEs from outside NYC are taught in ELA subjects, we only estimate the impact of MYEs from other districts on the math achievement of stable students. As shown in column 2, the estimated effects of MYEs from other U.S. districts (−0.40) and from other countries (−0.37) are of a similar magnitude but slightly larger than the estimated effect of MYEs from NYC. These results suggest that all three types of mid-year entry have a similar, negative impact on stable students' math achievement.

Mediation by MYE Characteristics

As already described, student achievement may be influenced by the demographic characteristics and achievement levels of peers, and MYEs tend to be more disadvantaged than stable students (Table 1). Thus, the estimated effects of mid-year entry may reflect not just the impact of that entry itself but also compositional changes in the student body. We address our third research question by including the demographic and educational characteristics of new entrants in the models.

Results for models that control for the demographic and educational characteristics of new entrants are shown in Table 4, columns 3 to 4 (math) and columns 7 to 8 (ELA). For both math and ELA, the estimated effect of the *overall* MYE ratio on stable students' math achievement is quite similar when controlling for MYE characteristics. For math, the point estimate is slightly smaller after controlling for the characteristics of MYEs (−0.24, column 3), while for ELA, the point estimate is slightly larger (−0.21, column 7).

TABLE 4

Mediation by the Characteristics of MYEs: Estimates of the Impact of Mid-Year Entry on Stable Student Achievement, Grades 4 to 8, 2005 to 2008

	Math				ELA			
	Main results		MYE characteristics		Main results		MYE characteristics	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MYE ratio	−0.28*** (0.04)		−0.24*** (0.04)		−0.19*** (0.04)		−0.21*** 0.04)	
MYE ratio—NYC		−0.25*** (0.05)		−0.18*** (0.04)		−0.18*** (0.04)		−0.15*** (0.04)
MYE ratio—United States		−0.40** (0.19)		−0.45*** (0.15)		N/A		N/A
MYE ratio—other country		−0.37*** (0.14)		−0.48*** (0.17)		N/A		N/A
MYE characteristics	N	N	Y	Y	N	N	Y	Y
Own characteristics	Y	Y	Y	Y	Y	Y	Y	Y
School characteristics	Y	Y	Y	Y	Y	Y	Y	Y
School-grade FE	Y	Y	Y	Y	Y	Y	Y	Y
Grade-year FE	Y	Y	Y	Y	Y	Y	Y	Y
School-year FE	Y	Y	Y	Y	Y	Y	Y	Y
Student FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	843,172	843,172	843,172	843,172	814,807	814,807	814,807	814,807
R^2	0.55	0.55	0.55	0.55	0.45	0.45	0.45	0.45

Note. Sample includes students who are observed in grades 4 to 8 for 3 or 4 years between 2005 and 2008. MYE characteristics include average lagged math and ELA test scores and the shares who are Black, Hispanic, Asian, poor, LEP, SPED, foreign born, and recent immigrant. Own characteristics include free and reduced-price lunch eligibility, recent immigrant status, LEP, and SPED. Time-varying school characteristics include the percentages of students who are Black, Hispanic, Asian, free lunch, reduced-price lunch, and LEP; the percentages of teachers with master's degrees and fewer than 3 years of experience; and the natural log of total school enrollment. Indicators are included to control for school grades with any MYEs and for schools that ever have no MYEs (magnet-type schools). The dependent variable is a student's test score measured as a *z*-score. Constant not shown. Standard errors in parentheses. ELA = English language arts; FE = fixed effects; LEP = limited English proficiency; MYE = mid-year entrant; NYC = New York City; SPED = special education.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

Next, we estimate a model using three origin-based MYE ratios. For math (column 4), the impact of MYEs from other NYC public schools is slightly attenuated after controlling for the characteristics of MYEs (−0.18). Point estimates for MYEs entering from other U.S. districts and from other countries increase somewhat in magnitude (−0.45 and −0.48, respectively). For ELA (column 8), the estimated effect of MYEs from other NYC public schools is very similar after controlling for characteristics of MYEs (−0.15). In all cases, the estimated coefficients across the different models are well within each other's confidence intervals. Thus, for both math and ELA, results from models with and without controlling for the characteristics of MYEs are qualitatively similar. We conclude that while the characteristics of new students may influence students' academic outcomes, our estimated effects are not driven by compositional changes in the student body.

Moderation by Characteristics of Stable Students: Subgroup Results

To determine if the characteristics of stable students moderate the impact of mid-year entry, we estimate the impact of the overall mid-year entry rate on various stable student subgroups (continuing to control for the characteristics of MYEs). For math (Table 5, Panel A), point estimates for Black (−0.14), Hispanic (−0.22), male (−0.25), female (−0.27), and poor students (−0.17) are statistically significant and similar to the estimated effect for the main sample (−0.24). We find somewhat larger negative impacts for White students (−0.52), Asian students (−0.59), and those ineligible for free or reduced-price lunch (−0.64). We find a similar pattern of results for ELA (Table 5, Panel B). Estimated coefficients for Black (−0.17), Hispanic (−0.18), Asian (−0.29), male (−0.24), female (−0.20), and poor students (−0.22) are statistically significant and similar to the point estimate for the main sample (−0.21). Once again, we find a larger negative effect for full-price lunch students (−0.52), but we find no impact for White students. Taken together, these results suggest that the impact of exposure to mid-year entry is somewhat larger for relatively advantaged students—a point we return to in the discussion.

Persistence in the Impact of Exposure to Mid-Year Entry

We next seek to shed light on the question of whether the impact of exposure to mid-year entry persists for multiple years. To do so, we estimate models controlling for contemporaneous and prior (lagged) exposure to mid-year entry. For math (Table 6, column 2), we find that the impact of exposure to mid-year entry in the prior academic year (−0.18) is nearly two thirds as large as the impact of exposure to mid-year entry in the current academic year (−0.28). For ELA, however, our results indicate that prior exposure to mid-year entry does not influence students' current achievement. Thus, for math only, the impact of exposure to MYE persists over time and suggests that repeated exposure to high mid-year entry rates over multiple years may substantially influence students' test scores.

Robustness Tests

To explore whether our results are sensitive to alternative measurement, modeling, and sample choices, we perform a series of robustness tests. Results are shown in Table 7, with our main results for math and ELA reproduced in columns 1 and 5 for comparison. We first explore the sensitivity of our results to different measurements of the MYE ratio. Instead of dividing the number of MYEs by the number of students enrolled in the school-grade in October, we use the number of students enrolled in the school-grade in June as an alternative denominator. For both math (−0.27, column 2) and ELA (−0.23, column 6), the estimated effect of mid-year entry using the alternative denominator is quite similar to the original results.[20] Thus, results are not sensitive to this alternative measure of the MYE ratio.

Next, because different types of student mobility may be correlated, one may be concerned that estimated effects conflate mid-year entry with overall school churn. For example, MYXs may negatively affect the achievement of stable students, potentially by harming classroom culture, by removing social supports, or by changing the composition of peers. In addition, students who are new to the school at the beginning of the school year may disproportionately absorb teachers' attention and indirectly harm their classmates' achievement. Because

TABLE 5

Moderation by Stable Student Characteristics: Estimates of the Impact of Mid-Year Entry on Stable Student Achievement, Grades 4 to 8, 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Math								
	Black	Hispanic	Asian	White	Male	Female	Poor	Not poor
MYE ratio	−0.14** (0.07)	−0.22*** (0.08)	−0.59*** (0.11)	−0.52*** (0.14)	−0.25*** (0.06)	−0.27*** (0.06)	−0.17*** (0.05)	−0.64*** (0.10)
Observations	264,479	333,584	123,534	121,575	416,688	426,484	682,659	160,513
R^2	0.23	0.30	0.40	0.27	0.55	0.55	0.50	0.68
Panel B: ELA								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Black	Hispanic	Asian	White	Male	Female	Poor	Not poor
MYE ratio	−0.17** (0.07)	−0.18** (0.07)	−0.29* (0.15)	0.02 (0.21)	−0.24*** (0.06)	−0.20*** (0.05)	−0.22*** (0.05)	−0.52*** (0.13)
Observations	263,410	314,645	117,445	119,307	401,848	412,959	658,725	156,082
R^2	0.23	0.29	0.33	0.25	0.46	0.46	0.39	0.55

Note. Sample includes students who are observed in grades 4 to 8 for 3 or 4 years between 2005 and 2008. All models include school-grade, grade-year, school-year, and student fixed effects. All models control for MYE characteristics, own characteristics, and school characteristics. MYE characteristics include average lagged math and ELA test scores and the shares who are black, Hispanic, Asian, poor, LEP, SPED, foreign born, and recent immigrant. Own characteristics include free and reduced-price lunch eligibility, recent immigrant status, LEP, and SPED. Time-varying school characteristics include the percentages of students who are Black, Hispanic, Asian, free lunch, reduced-price lunch, and LEP; the percentages of teachers with master's degrees and fewer than 3 years of experience; and the natural log of total school enrollment. Indicators are included to control for school grades with any MYEs and for schools that ever have no MYEs (magnet-type schools). The dependent variable is a student's test score measured as a z-score. Constant not shown. Standard errors in parentheses. ELA = English language arts; LEP = limited English proficiency; MYE = mid-year entrant; SPED = special education services.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

TABLE 6

Persistence in Effects: Estimates of the Impact of Mid-Year Entry and Lagged Mid-Year Entry on Stable Student Achievement, Grades 4 to 8, 2005 to 2008

	Math		ELA	
	(1)	(2)	(3)	(4)
MYE ratio	−0.24*** (0.04)	−0.28*** (0.04)	−0.21*** (0.04)	−0.21*** (0.05)
Lagged MYE ratio		−0.18*** (0.05)		0.00 (0.04)
MYE characteristics	Y	Y	Y	Y
Own characteristics	Y	Y	Y	Y
School characteristics	Y	Y	Y	Y
School-grade FE	Y	Y	Y	Y
Grade-year FE	Y	Y	Y	Y
School-year FE	Y	Y	Y	Y
Student FE	Y	Y	Y	Y
Observations	843,172	843,172	814,807	814,807
R^2	0.55	0.55	0.45	0.46

Note. Regressions use the main analytic sample (students in the panel 3–4 years from 2005 to 2008); results are similar when using the full sample of all students in these grades and years. Each column includes only one grade of students. MYE characteristics include average lagged math and ELA test scores and the shares who are black, Hispanic, Asian, poor, LEP, SPED, foreign born, and recent immigrant. Own characteristics include free and reduced-price lunch eligibility, recent immigrant status, LEP, and SPED. Time-varying school characteristics include the percentages of students who are Black, Hispanic, Asian, free lunch, reduced-price lunch, and LEP; the percengtages of teachers with master's degrees and fewer than 3 years of experience; and the natural log of total school enrollment. Indicators are included to control for school grades with any MYEs and for schools that ever have no MYEs (magnet-type schools). The dependent variable is a student's test score measured as a *z*-score. Constant not shown. Standard errors in parentheses. ELA = English language arts; FE = fixed effects; LEP = limited English proficiency; MYE = mid-year entrant; SPED = special education.
**p* < 0.1. ***p* < 0.05. ****p* < 0.01.

these types of student mobility may have independent effects on the achievement of stable students (and are correlated with mid-year entry), we estimate models that control for the MYX ratio and the summer entry ratio. Results demonstrate that the estimated effect of mid-year entry is essentially unchanged after these controls are included, both in math (−0.24, column 3) and ELA (−0.22, column 7). Results from this robustness test indicate that our estimated effects of mid-year entry are robust to including additional measures of school instability.

Finally, we explore whether results are robust to the choice of analytic sample. In columns 4 and 8, we show results for a sample of all fourth-through eighth-grade students from 2005 to 2008, including students who are only observed for 1 or 2 years. Estimated effects are slightly smaller in magnitude using this full sample, with estimated coefficients of −0.13 for math and −0.15 for ELA. Taken together, the robustness tests indicate our results are not sensitive to these choices about measurement, model specification, or analytic sample. All models support the conclusion that exposure to mid-year entry has a small but meaningful negative impact on stable students' math and ELA achievement.

Discussion

Results provide convincing evidence that new students who enter during the school year negatively affect the achievement of stable students. Importantly, our results are robust to controlling for the characteristics of MYEs, suggesting that there is a disruptive effect of mid-year entry beyond any influence of changes in peer characteristics. Estimated coefficients are similar in magnitude to results from previous studies. For example, Hanushek et al. (2004) use a similar approach to measuring student test scores and mid-year entry rates and report a coefficient of −0.14, which translates to an estimated average effect in math of approximately −0.01 SDs (quite similar to our results); Raudenbush et al. (2011)

TABLE 7

Robustness Tests: Estimates of the Impact of Mid-Year Entry on Stable Student Math Achievement Under Alternative Measurement, Modeling, and Sample Decisions, Grades 4 to 8, 2005 to 2008

	Math				ELA			
	Main results	June denominator	School churn	Full sample	Main results	June denominator	School churn	Full sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MYE ratio	−0.24*** (0.05)	−0.27*** (0.05)	−0.24*** (0.04)	−0.13*** (0.04)	−0.21*** (0.04)	−0.23*** (0.04)	−0.22*** (0.04)	−0.15*** (0.03)
MYX ratio			−0.12** (0.05)				0.06 (0.04)	
Summer entry ratio			−0.00*** (0.00)				−0.34*** (0.00)	
MYE characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Own characteristics	Y	Y	Y	Y	Y	Y	Y	Y
School characteristics	Y	Y	Y	Y	Y	Y	Y	Y
School-grade FE	Y	Y	Y	Y	Y	Y	Y	Y
Grade-year FE	Y	Y	Y	Y	Y	Y	Y	Y
School-year FE	Y	Y	Y	Y	Y	Y	Y	Y
Student FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	843,172	843,172	843,172	1,323,012	814,807	814,807	814,807	1,268,888
R^2	0.55	0.55	0.55	0.59	0.45	0.45	0.45	0.51

Note. The analytic sample used in columns 1-3 and 5-7 includes students who are observed in grades 4 to 8 for 3 or 4 years between 2005 and 2008. The full sample used in columns 4 and 8 includes all students in grades 4-8 in these years. MYE characteristics include average lagged math and ELA test scores and the shares who are black, Hispanic, Asian, poor, LEP, SPED, foreign born, and recent immigrant. Own characteristics include free and reduced-price lunch eligibility, recent immigrant status, LEP, and SPED. Time-varying school characteristics include the percentages of students who are Black, Hispanic, Asian, free lunch, reduced-price lunch, and LEP; the percentages of teachers with master's degrees and fewer than 3 years of experience; and the natural log of total school enrollment. Indicators are included to control for school grades with any mid-year entrants and for schools that ever have no mid-year entrants (magnet-type schools). The dependent variable is a student's test score measured as a *z*-score. Constant not shown. Standard errors in parentheses. ELA = English language arts; FE = fixed effects; LEP = limited English proficiency; MYE = mid-year entrant; MYX = mid-year exiter; SPED = special education.

*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

also find a small negative effect of mid-year entry. Furthermore, our results indicate that the spillover effect of MYEs is similar in magnitude to the spillover effect of troubled peers, who also may disrupt classroom environments. For example, Carrell and Hoekstra (2010) conclude that in a classroom of 20 students, one additional classmate who is exposed to domestic violence at home reduces the test scores of peers by approximately 0.025 *SD*s. Similarly, Fletcher (2010) finds that having at least one classmate with an emotional disturbance reduces math test scores by approximately 0.06 *SD*s and reading test scores by approximately 0.03 *SD*s.

In NYC, most students are not substantially affected by new student entry in the short run, but entrants can meaningfully influence the achievement of stable classmates at the high end of the instability distribution, in aggregate, and over the long run. Compared to a student with average exposure to mid-year entry (0.033 in 2008), a student exposed to a high MYE ratio (0.083 at the 95th percentile) will have math test scores reduced by 0.01 *SD*s. This is not a large effect for an individual student, but because all students in the grade experience this high mid-year entry, the effect (summed over all students) can be sizable. Furthermore, in a large city like NYC, the very top of the distribution represents a large group; for example, across all years in our analytic sample, more than 36,000 students experience MYE ratios greater than 0.08.

We also find the impact of exposure to mid-year entry continues to influence the math achievement of stable students for multiple years. One potential explanation for this phenomenon in math but not ELA is that in mathematics, concepts tend to build on one another; if students do not master specific concepts, their ability to develop more advanced problem solving skills will be compromised. Our findings suggest that effects can accumulate, with exposure to high mid-year entry for 2 years being particularly harmful for students' math performance.

An important contribution of this study is its attention to heterogeneity in impacts, as we examine differences in how new students who arrive from other NYC public schools, from other school systems in the United States, and from outside the country influence the math achievement of their peers. Compared to MYEs from NYC, we find that MYEs from other U.S. school districts and from out of the country have slightly larger negative impacts on math performance. These results are consistent with a mechanism in which students arriving from less similar schools are more disruptive, perhaps because students who have made greater changes likely require more teacher attention than entrants from within the district. Compared to students transferring across NYC public schools, children arriving from other school systems may have more difficult transitions; for example, they are less likely to be using a similar curriculum and may have less stability in friend groups and social supports.

Previous studies have been limited in their ability to estimate effects by student subgroup, and a key contribution of this study is its attention to the moderating effects of stable student characteristics. The subgroup results highlight the important issue of the difference between *exposure* to mid-year entry and the *impact* of mid-year entry. In our subgroup analyses, we estimate larger coefficients on mid-year entry for groups who are typically exposed to lower rates (Asian and non-poor students).[21] From an empirical perspective, this result is perhaps not surprising, as our analytic approach uses random fluctuations in students' exposure to mid-year entry over time, netting out the influence of students' typical exposure. From a practical perspective, these results suggest that disruption is relative: the marginal effect of one additional new student arriving during the academic year is smaller in grades with greater student churn. It is important to recognize that large point estimates for groups who seldom experience high mid-year entry will not translate to particularly large effects on test scores. The students most negatively affected by new entrants are those exposed to very high rates, and these students are disproportionately Black, Hispanic, and poor. Thus, variation in exposure to mid-year entry has clear equity implications for poor and minority students.

Conclusion

While student mobility has long been considered an important factor affecting the achievement of mobile students themselves, it is increasingly understood to influence the achievement of stable students as well. In this article, we estimate the spillover effect of MYEs, who may be particularly disruptive to the progress of their stable peers. We conclude that while for most students mid-year entry is not having a major negative effect on test scores in the short run, the impact for students exposed to relatively high mid-year entry is much more meaningful. Furthermore, there is suggestive evidence that negative effects accumulate over time. We also find that some types of entry are more detrimental than others, with larger negative effects of new students from other U.S. districts and from other countries. Our estimated effects are slightly mediated by the demographic characteristics and achievement levels of new entrants, suggesting that changes in peer composition can influence student test scores, although there continues to be a unique impact of mid-year entry beyond what is explained by changes in classmates' characteristics.

Our results suggest several areas for future research. First, it would be useful to know whether and to what extent mid-year mobility affects stable students' non-cognitive outcomes. For example, school instability might influence students' attitudes and behaviors, which could ultimately result in impacts on outcomes such as attendance and suspensions. Furthermore, while this article focuses on the spillover effects of mid-year entry, it is also important to understand if MYEs are particularly harmed by moving to highly volatile schools.

In addition, we show that variation in the impact of MYEs by stable student characteristics is not driven by the characteristics of MYEs; that is, even after controlling for the characteristics of MYEs, some groups of stable students are particularly negatively affected by mid-year entry. It would be useful to explore two hypotheses. First, differences in impacts could emerge because of differences in institutional characteristics, with larger negative effects in schools that are not accustomed to instability and therefore have less capacity to manage student transitions. Second, effects may vary because of differences in unobserved stable student characteristics, with larger negative effects for students who are not accustomed to instability or chaotic school environments more generally.

Finally, future research should explore different approaches to reducing negative spillovers of mid-year entry. Some policy responses may target reducing *exposure* to high mid-year mobility, such as allowing students to remain in their original schools when they make residential moves or distributing new entrants more evenly across schools. Other administrative responses may seek to minimize the negative *effect* of mid-year entry. For example, structures to smooth transitions for new students (e.g., meetings with counselors, structured orientations) and additional classroom resources (e.g., teacher aides, smaller class sizes, technologies that personalize learning) may benefit both movers and their stable peers. Research on these policies and interventions may help provide helpful guidance for administrators and policymakers who are considering different responses to student mobility.

Technical Appendix

To explore the validity of our identification strategy, we regress the MYE ratio on average school-grade characteristics, both with and without school-grade, grade-year, and school-year fixed effects. The logic of this test is that because mid-year entry is not randomly distributed, when we do not include fixed effects, MYE ratios are likely to be significantly related to average student characteristics. If the fixed effects allow us to isolate random variation in entry rates, however, once we include the set of two-way fixed effects in the model, student characteristics should not be significantly related to the MYE ratio. A similar balancing test is used by Hu (2015) in a study of gender peer effects.

Results from this test, shown in Table A1, indicate that without fixed effects, mid-year entry is significantly related to many average student characteristics; based on results from an F-test, we reject that student characteristics taken jointly are unrelated to the MYE ratio. (We reject the null hypothesis that all coefficients are jointly equal to zero, as the p value is less than 0.001.) Thus, one is correct to be concerned that mid-year entry is related to student characteristics. Once we include school-by-grade, grade-by-year, and school-by-year fixed effects, however, results from the joint F-test indicate that we cannot reject the hypothesis that, taken together, student characteristics are unrelated to the MYE ratio ($p = 0.194$). The same results hold for the origin-based MYE ratios. That is, we cannot reject the hypothesis that student characteristics (taken jointly) are unrelated to MYE ratios. These results provide support for our identification strategy, suggesting that including the set of two-way fixed effects allows us to isolate plausibly random variation in mid-year entry ratios.

TABLE A1

Balancing Test: Estimates of the Relationship between Mid-Year Entry and Average Student Characteristics, Grades 4 to 8, 2005 to 2008

	MYE ratio		MYE ratio—NYC		MYE ratio—United States		MYE ratio—other country	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of October students who are								
Black	0.012***	−0.007	0.009***	−0.010	0.001**	0.001	0.002**	0.001
	(0.002)	(0.013)	(0.002)	(0.012)	(0.000)	(0.004)	(0.001)	(0.003)
Hispanic	−0.004**	−0.003	−0.003	−0.006	−0.000	0.000	−0.001	0.002
	(0.002)	(0.012)	(0.002)	(0.011)	(0.001)	(0.004)	(0.001)	(0.003)
Asian	0.012***	0.019	0.011***	0.017	0.000	−0.000	0.000	0.002
	(0.003)	(0.013)	(0.002)	(0.011)	(0.001)	(0.004)	(0.001)	(0.004)
Female	−0.018***	−0.007	−0.013***	−0.001	−0.004***	−0.004*	−0.001	−0.001
	(0.005)	(0.007)	(0.004)	(0.006)	(0.001)	(0.002)	(0.002)	(0.003)
LEP	0.013*	0.006	−0.011**	−0.006	0.008***	0.003	0.016***	0.009
	(0.007)	(0.018)	(0.005)	(0.013)	(0.002)	(0.005)	(0.003)	(0.006)
SPED	0.006	−0.004	0.002	−0.002	0.001	−0.000	0.004**	−0.002
	(0.006)	(0.010)	(0.005)	(0.009)	(0.001)	(0.003)	(0.002)	(0.003)
Free lunch	0.001	−0.000	0.002*	0.005	−0.001*	−0.005*	−0.000	−0.001
	(0.001)	(0.009)	(0.001)	(0.008)	(0.000)	(0.003)	(0.000)	(0.002)
Reduced-price lunch	−0.012**	0.006	−0.014***	0.009	−0.001	−0.005	0.003**	0.002
	(0.004)	(0.013)	(0.004)	(0.012)	(0.001)	(0.004)	(0.001)	(0.004)
Foreign-born	−0.056***	−0.021*	−0.040***	−0.019*	−0.005**	−0.002	−0.011**	−0.001
	(0.008)	(0.013)	(0.005)	(0.011)	(0.002)	(0.005)	(0.005)	(0.004)
Recent immigrant	0.192***	0.070***	0.064***	0.055***	0.027***	0.004	0.100***	0.011
	(0.024)	(0.025)	(0.009)	(0.020)	(0.006)	(0.006)	(0.018)	(0.008)
Average lagged z-math	−0.003	−0.003	−0.004**	−0.002	−0.001**	−0.001	0.002***	−0.000
	(0.002)	(0.003)	(0.002)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)
Average lagged z-read	−0.019***	−0.000	−0.019***	−0.002	0.000	0.002	−0.001	−0.000
	(0.002)	(0.004)	(0.002)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)
Fixed effects	N	Y	N	Y	N	Y	N	Y
p-value for joint F-test	0.000	0.194	0.000	0.179	0.000	0.504	0.000	0.611
Observations	10,675	10,675	10,675	10,675	10,675	10,675	10,675	10,675
R^2	0.197	0.777	0.157	0.754	0.068	0.651	0.320	0.826

Note. Models use school-grade-level data. Fixed effects include school-grade, grade-year, and school-year. The null hypothesis for the joint F-test is that all coefficients are jointly equal to zero. The dependent variable is the MYE ratio. Constant not shown. Robust standard errors in parentheses. LEP = limited English proficiency; MYE = mid-year entrant; NYC = New York City; SPED = special education.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$, clustered at school-grade-year level.

Authors' Note

All conclusions are the authors' alone.

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Notes

1. For example, Alexander, Entwisle, and Dauber (1996), Hanushek, Kain, and Rivkin (2004), Kerbow (1996), Nelson, Simoni, and Adelman (1996), Pribesh and Downey (1999), Rockoff and Lockwood (2010), Rumberger and Larson (1998), Schwartz, Stiefel, and Cordes (2016), Schwartz, Stiefel, Rubenstein, and Zabel (2011), Swanson and Schneider (1999), Temple and Reynolds (2000).

2. The other main approach to estimating peer effects relies on random assignment of students to groups; see Carrell, Fullerton, and West (2009), Gottfried (2013a, 2014), and Sacerdote (2001).

3. Test scores are measured in *z*-scores, which are standardized to have a mean of 1 and a standard deviation of 1 across all students in New York City (NYC) for each grade-year combination.

4. All students in our sample attend a NYC public school in March; due to data constraints, those who exit the district before March are not included in the sample.

5. The register as of October 31 is a major determinant of funding for the year.

6. Middle school class codes identify students' homerooms. Note that the grade-level measure of mid-year entry may not be as appropriate in a high school setting, where students in different grades often take the same courses. In this study, we include only elementary and middle school grades.

7. We do not include full-time special education students in exclusively self-contained classrooms, who do not take exams, or charter school students, who are not included in the databases for these years.

8. Results for 2005 to 2007 are similar; they are not shown but are available from the authors.

9. This is a common configuration for elementary school grades. In 2008, for example, the average school-grade had 120 students enrolled in October and 3.9 mid-year entrants. According to the NYC Department of Education's 2007 to 2008 class size report, the average class size in grades 4 to 8 was 28.1 students (New York City Department of Education, 2008), suggesting 3 to 4 classes per grade is typical.

10. In 2008, the bottom decile of non-zero mid-year entry includes MYE ratios greater than zero and less than or equal to 0.011; the top decile includes MYE ratios of at least 0.070.

11. Using school-grade-year level data, the mid-year entry ratio is positively correlated to both the mid-year exit ratio (correlation coefficient = .244) and the beginning-of-year entry ratio (correlation coefficient = .118).

12. Value-added models are a common alternative to student fixed effects models; see Todd and Wolpin (2003).

13. Magnet-type schools have at least one year from 2005 to 2008 in which they receive zero MYEs at the school level. Investigation of school policies indicates these schools have restricted or screened admissions criteria, for example requiring students to audition or meet test score requirements. There are 89 magnet-type schools in the sample.

14. This is similar to the approach used by Hanushek et al. (2004) and is preferable to a simpler model that includes only school, grade, and year effects.

15. With this approach, we calculate the average effect of mid-year entry for students exposed to the mean MYE rate and MYEs with mean characteristics. An alternative is to interact the mid-year entry ratio with MYE characteristics. Results from both approaches are nearly identical. For ease of interpretation, we present the more straightforward model, which controls for MYE characteristics.

16. This is similar to estimating a model that interacts the mid-year entry ratio and all other variables in the model with a subgroup characteristic of stable students.

17. We do not restrict the sample to students who make standard academic progress because such a group would be higher achieving than NYC stable students overall and thus not representative.

18. Results are similar when we allow for non-linearity by including a quadratic term of the MYE ratio.

19. To calculate this effect, we multiply the increase in the MYE ratio by the reported coefficient. For example, $0.05 \times 0.20 = 0.01$.

20. Results are also similar when using the number of students ever enrolled in the school-grade during the academic year as the denominator.

21. This contrasts with Raudenbush, Jean, and Art (2011), who find that low-scoring African American children are most negatively affected by new student arrivals. This may be because we control for the characteristics of mid-year entrants, including prior academic achievement, whereas they do not.

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