SCHOOL CHOICE, STUDENT SORTING AND ACADEMIC PERFORMANCE[†]

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Abstract

This paper examines the general equilibrium effects of school choice on student academic performance. I use the universe of admission and graduation records between 2004 and 2019 from Romanian high schools, where students compete for high school seats of their choice. By exploiting quasi-random differences in the number of schools students can choose from across towns with similar student populations, I generate two main findings: i) having more schools to choose from leads to more sorting by test scores across schools and ii) sorting exacerbates inequalities in academic outcomes between high- and low-scoring students. I confirm these findings using school openings in small towns. A new school opening exacerbates sorting by admission scores across schools and widens achievement gaps. Lastly, I explore the channels underlying these effects. Using random variation in cohort admission scores, I show that peer effects explain part of the widening of test score gaps across schools. Then, I link teacher hiring records and school spending data to show that high-ability teachers sort into more selective schools and boost graduation test scores, while school spending has little effect.

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1 Introduction

School choice remains one of the most controversial topics in education. Proponents of school choice argue that since public schools are inefficient monopolies, allowing parents to choose between schools would exert competitive pressures on them and act as a "rising tide that lifts all boats". On the other hand, in the presence of geographic constraints limiting student mobility, imperfect information regarding school effectiveness, parental preferences over peers, informational asymmetries and school preferences over children, school choice may increase the stratification of students across schools by ability, race or socioeconomic characteristics, potentially widening inequalities. Teasing out the effects of school of school choice has proven to be elusive both because of a lack of data allowing researchers to measure the *distributional* effects on students and because quasi-experimental variation in school choice is difficult to come by.

In this paper, I ask whether school choice is indeed a "rising tide that lifts all boats" or merely exacerbates existing educational inequalities. I do so in the context of Romanian high schools. In Romania, all prospective high school students compete for high school seats of their choice and are assigned to their most preferred available seat via a serial dictatorship rule, which prioritizes students with high scores on a standardized admission exam. The more schools there are in a town, the easier it is for high-scoring students to sort into selective schools, away from their low-scoring counterparts. I exploit quasi-random variation in the number of high schools students can choose from across similar localities to i) measure how varying degrees of school choice impact student sorting patterns, ii) the impact of this sorting on academic outcomes and iii) what are the plausible channels through which school choice-induced sorting affects academic outcomes.

Using rich data containing individual-level admission and graduation records from Romanian high schools between 2004 and 2019 allows me to make several contributions to the literature. First, since Romanian students write national, standardized high school admission and graduation exams, I am able to estimate the effects of school choice not only on mean outcomes but also on student sorting across schools and their academic achievement across the entire ability distribution. While two separate strands of literature focus on the effects of school choice on student sorting (e.g. Urquiola 2005, and MacLeod and Urquiola 2015) and mean learning outcomes (e.g. Hoxby 2000, Hsieh and Urquiola 2003 and Rothstein 2007), often with contradictory findings, few studies have shown the distributional impact of school choice-induced sorting on student outcomes. Since the effects of school choice on mean achievement found by previous literature tends to be modest and a large literature[1] predicts that the school choice may mainly widen inequalities, access to individual-level outcomes allowing for a more in-depth analysis of distributional impacts becomes paramount.

Second, I disentangle some of the channels that plausibly affect student outcomes. To do this, I link the student data to administrative data to two novel data sources. I first use administrative data on teacher hiring that contains rich information on teacher ability, education level, grades and experience. Teachers compete for teaching jobs via a standardized written and oral subject-specific exam designed to measure their teaching ability and apply to high schools of their choice, with high-scoring teachers having priority over teaching jobs. This allows me to measure how teachers sort across high schools, contrast this sorting to student sorting and measure its potential impacts on student achievement. I then use data on school spending data,

[1] For example, Epple and Romano (1998), Rothstein (2006), Altonji et al. (2015), MacLeod and Urquiola (2015), Allende (2019) and MacLeod and Urquiola (2019).

which allows me to measure how material resources are allocated across schools, how these mirror student and teacher sorting patterns and measure associations between school spending and student achievement. Thus, with peer effects, I can analyze three potential channels through which school choice-induced sorting affects academic outcomes.

I exploit quasi-random variation in the number of schools across similar-sized towns, which essentially provides students with different degrees of school choice. I begin by showing that the variation in the number of schools across similar-sized towns in Romania is exogenous for three reasons. First, baseline student characteristics across towns with similar populations, but a different number of schools are not statistically different: both the mean and the distribution of admission scores across these different types of towns are the same. Therefore, there is no evidence that household sorting across locations is related to differences in the number of schools across similar towns. Second, using census data I show that Romanian households are relatively geographically immobile and not strongly sorted by socioeconomic characteristics across similar towns. High home ownership rates dating to dwelling allocation at the end of the communist regime play an important role in this immobility. Lastly, I show that the number of schools has largely been frozen since the 1970s, even though large demographic and economic changes have impacted different regions differently. Indeed, changes in demographics across towns between 1990 and 2019, while large, are not correlated with changes in the number of schools across locations, which is mostly fixed.

Thus, i) differences in the number of high schools across similar-sized towns not correlated with the distribution of student scores across towns, ii) household sorting across towns is limited and iii) the number of schools is highly invariant, predetermined and uncorrelated with demographic and economic changes in the past thirty years. I use this exogenous variation in school numbers across similar localities in an instrumental variable framework to show how having more - or fewer - schools to choose from impacts student sorting patterns and academic outcomes. I confirm these findings by exploiting the few high school openings in small towns, which disrupt student sorting patterns.

Having established the plausibility of exoegenity of the number of schools across similar localities, I continue by showing that school choice leads to more student sorting by test scores across schools. First, the reshuffling of students between the end of middle school and the beginning of high school leads to a dramatic increase in student segregation by test scores. Thus, within towns, high school choice leads to dramatically more sorting by test scores across high schools than across middle schools, where students are assigned via a neighborhood assignment mechanism. Second, across towns, the more high schools students can choose from, the more pronounced the sorting is across schools. The mechanism underlying this process is simple: the more high schools there are in a given market, the more competitive admissions to very selective schools are. High-score students can sort into these high schools, while their low-scoring counterparts are increasingly relegated to low-quality schools. This result is confirmed by school openings: after a new school opens in a small town, student sorting across schools increases. The difference in sorting is most pronounced when comparing one-high school towns, where there is essentially no school choice, and two-high school towns, where a significant amount of sorting across test scores becomes possible.

I then show that this school-choice induced sorting ultimately leads to increased outcome inequalities, with low-admission score students falling farther and farther behind their high-score counterparts. Using an instrumental variable approach, I estimate that school choice in large cities, where sorting is the most severe, leads to an 8 percentile widening of the high school graduation test score gaps between high- and low-admission score students. When considering within-school across-track sorting, this number increases to 14 percentiles. Studying school openings in small towns in a triple difference framework confirms these findings. After a new school opens, sorting increases markedly, and the graduation exam score gap between high- and low-admission score students increases markedly, by around 9 percentiles.

Additionally, I disentangle the channels through which school choice-generated student sorting affects academic performance. The rich data in the Romanian setup allow me to speak to three possible channels: peer effects, differences in teacher ability and school expenditure. I first use admission scores across cohorts admitted to the same track in different years to identify peer effects. Students admitted to one-classroom tracks who happen to have higher-admission score peers tend to score higher on the graduation exam.

Then, I use teacher hiring records and their results on a national subject-specific placement exam that determines the school they are assigned to. I show that teachers sort by placement scores across schools. Schools attended by high-scoring students hire high-scoring teachers; this sorting is more pronounced in locations with more high schools. Thus, teacher sorting closely mirrors student sorting and high-scoring students in locations with many high schools are more likely to be taught by high-scoring teachers than their counterparts in smaller towns. Lastly, I show evidence that conditional on admission scores, teacher placement scores are highly correlated with graduation scores, while other teacher characteristics (such as college GPA, experience and education) are not. Lastly, I show that while there is a significant amount of variation in spending across schools, this spending is not correlated with student achievement.

This paper speaks to three main strands of literature. The first one is the literature on school choice. A large body of literature discusses the efficiency gains generated by school choice, with some studies finding evidence for increase in mean test scores (e.g. Hoxby 2000, Campos and Kearns 2022), while others find no effect or explore the theoretical reasons why, in the presence of peer effects, asymmetric information and other market frictions, such gains will be modest (Hsieh and Urquiola 2003, Rothstein 2006). In light of this, other studies have focused on the effects of school choice on student sorting and stratification (MacLeod and Urquiola 2015, Altonji et al. 2015, Barseghyan et al. 2019, MacLeod and Urquiola 2019, Abdulkadiroğlu et al. 2020 and Machado and Szerman 2021), especially since a large body of theoretical literature predicts the reallocation of students across schools to be the main effect of school choice, rather than efficiency gains.

The rich Romanian data allows me to link these two strands of literature. Indeed, I first find that school choice accentuates student sorting on scores and then proceed to show its effects on student learning outcomes. While I do not find any differences in mean scores across localities with differences in the degree of school choice student have, I find that school choice increases the variance of test scores, accentuating the differences between high- and low-ability students.

Another relevant strand of literature is the literature on attending a better school. Attending a better school improves academic outcomes (for example Deming et al. 2014 and Pop-Eleches and Urquiola 2013 in the Romanian context, among many others). We contribute to this literature by providing general-equilibrium evidence that allowing high-ability students to sort into better schools progressively improves their test scores.

Lastly, I contribute to the literature on tracking. Indeed, the Romanian admission mechanism essentially creates tracking by ability between different high schools. While Duflo et al. (2011) suggests that in some contexts where students are of very different abilities, tracking may benefit everyone, my results suggest that tracking, especially when associated with a potential disparity of resources among different tracks, may lead to a widening gap between high- and low-scoring students. This different result can be rationalized by the fact that unlike in Duflo et al. (2011), teaching and other school resources are allocated endogenously. Moreover, while in the Kenyan context, students are of very heterogeneous ability levels and even ages which might drive the effectiveness of tracking by ability. In contrast, the Romanian high school student population is much more homogeneous and peer effects might dominate the benefits of tracking.

To conclude, the rich nature of the Romanian high school data allows me to unearth a link between school choice and increasing inequality in access to quality schools and, ultimately, increased inequalities in outcomes between high- and low-scoring students. The Romanian high school system, which combines school choice with exam-based admissions, serves as a cautionary tale: the efficiency gains from school choice can easily be dwarfed by the increase in score dispersion, with the most vulnerable students emerging as losers. Since tens of millions of students worldwide, from Chinese and Turkish high school-bound students to US and Brazilian college-bound students, are assigned to schools via a competitive admission process similar to the Romanian high school assignment each year, the implied increase in educational outcome inequalities is significant. Policymakers thus need to keep in mind that unless steps are taken to ensure equitable access to good quality schools, school choice is likely to serve as one more mechanism through which segregation and educational disparities propagate.

The remainder of this paper is structured as follows. Section 2 describes the Romanian high school system and the data sources used. Section 3 highlights student sorting and student achievement patterns prevalent in the data. Section 4 lays out the two identification strategies, while section 5 highlights the main results. Section 6 explores different channels through which school choice-induced sorting affects student outcomes. Lastly, section 7 provides a discussion and conclusion.

2 Setup and Data

Each year, Romanian middle school graduates, who complete 8^{th} grade, are assigned to high schools based on a unique centralized mechanism. Each student receives an admission score. This score has two components: first, their middle school (grades 5-8) GPA and, second, a score on a national, standardized high school admission exam covering different subjects (mathematics, Romanian, and, in some years, a choice between history or geography). The admission score places different weights on the two components in different years, but at least half of the total score is attributed to the admission exam.

After writing the exam and receiving their admission scores, students fill out an essentially untruncated list of ranked preferences over combinations of high schools and tracks they wish to attend. Tracks include, but are not limited to: mathematics and computer science, literature, natural sciences, social sciences and many technical or service tracks. For example, a student can rank the literature track in high school A as their first choice, the literature track in high school B as their second choice and the science track in high school A as their third choice.

After collecting student preferences, a centralized algorithm allocates students to high school seats. First, students are ranked in descending order of their admission scores. Then, starting with the top-ranked student, each student is assigned a seat in their most preferred high school track that a higher-ranked student has not already filled.[2] There are no other geographic, socioeconomic or family criteria used to assign students to schools. This mechanism ensures that high-scoring students have absolute priority over lower-admission score students. Moreover,

[2]The assignment mechanism is equivalent to a serial dictatorship.

students have no incentive to strategically manipulate their preferences over tracks in the hope of a better assignment.[3] Finally, if schools prefer admitting students with higher scores to those with lower scores, the algorithm ensures match stability, in the sense that no seat trades can be made such that the new allocation is preferred to the old allocation by both students and schools.

2.1 High School Graduation Exam

After completing four years of high school (grades 9-12), Romanian high school students register to take a national, standardized high school exit exam. This is a high-stakes exam. This exam consists of several subjects, including Romanian, mathematics, and other track-specific subjects. Receiving a high school diploma is contingent on passing this exam (obtaining a grade of at least 50% on every component). Moreover, the exit exam grade exam can be used as an admission requirement for students planning to attend postsecondary schooling. This exam is thus high stakes and helps compare student learning at high school graduation. The admission and graduation exams from one town are sent to different, randomly selected towns to avoid conflicts of interest in grading.

2.2 Teacher Allocation

I collect data on teacher hiring to further analyze how student sorting across schools affects their performance. Each year, teachers in Romania are assigned to high school teaching jobs via a standardized subject-specific examination consisting of an oral and a written component. Although the teacher allocation mechanism is slightly more complicated than the student one,[4] high-scoring teachers generally have priority over low-scoring ones in choosing the school where they work. Salaries are standardized for all teachers, so teacher preferences do not reflect salary considerations.

I scraped data on all teacher hires in Romania from 2015 to 2019. These include the placement test results, placement outcomes and individual characteristics of close to 200,000 prospective teachers competing for 40,000 teacher jobs across Romanian high schools. Characteristics include college GPA, experience, education level and results on other qualification exams used by teachers to achieve higher pay grades.

2.3 School Spending

I also use school spending information to measure how resources are allocated across schools and how these impact student performance. To this end, I scraped the Romanian Electronic Purchase System (SEAP). According to EU legislation, all public institutions, including schools, must publicly post their expenditures on goods and services. I obtained more than one million school transactions, ranging from purchases of utilities and food to classroom material and renovations, between 2008 and 2019. These data enable me to explore the link between school spending and student outcomes.

[3] In other words, the mechanism is incentive compatible.

[4] For example, there is priority given to teachers who want to return to their hometown and to temporary teachers who want to apply for permanent jobs in their current schools and meet some minimum criteria.

Table 1: Summary of Data

Number of High Schools in Town	1	2	3	4-15	16+
Towns (Yearly)	344.2	56.1	26.2	53.6	19.3
High Schools	1.0	2.0	3.0	8.7	47.9
Middle Schools	4.0	4.5	4.9	7.9	49.5
Tracks (per High School)	1.5	1.7	1.8	1.8	1.7
Matched Students	180,191	94,893	82,769	370,795	487,573
Yearly Exit Exam Students (per Town)	46	141	264	577	2102
Yearly Exit Exam Students (per School)	46	76	99	97	96
Yearly Exit Exam Students (per Track)	18	22	24	25	28
Admission Exam Score (Percentile)	49	57	59	61	64
Exit Exam Score (Percentile)	48	56	57	59	62
Exit Exam Pass Rate (%)	60	72	73	75	80
Hired Teachers (Total)	5,050	1,680	969	5,339	6,957
Yearly Hired Teachers (per Town)	3.1	6.3	9.1	21.8	133.8
Yearly Hired Teachers (per School)	3.1	3.1	3.0	3.0	4.5
Teacher Score (Percentile)	47	47	49	49	54
Total Town Spending (EUR 000s)	79	154	98	359	2,418
Total School Spending (EUR 000s)	79	92	37	56	91
Spending per Student (Town)	533	950	199	548	1,774
Direct Spending per Student (Town)	461	681	128	482	250

Note: This table contains summary statistics of the admission, graduation, teacher and spending records. Student number statistics are given for students with matched admission and graduation records and who do not switch high schools. I include all students in high schools that require the high school admission exam and whose students take the high school exit exam at graduation. These include regular high schools, but also some vocational schools. Admission, exit and teacher exam scores are calculated as percentiles at the year-national level. School spending can be direct (for smaller, day-to-day amounts) or by contract (for larger expenditures, such as renovations).

2.4 Data

I match more than two million student admission (2004-2015) and graduation records (2008-2019).[5] The data include middle school attended by students (and by extension, their location in middle school), middle school GPA, admission and exit exam grades (by component) and high school and track student was assigned to. This implies that it is possible to observe students migrating from their town of residence in middle school to attend high school. In a later section, I study how students migrating across towns affects my results concerning student sorting and differences in outcomes.

I restrict my analysis to matched students.[6] I complement these data with yearly data on town population, high-school dropout rates, unemployment rates and county-level wage rates.

The data are summarized in Table 1. Since I will later use variation in the number of high schools across different locations, the summary statistics are broken down by towns with different numbers of high schools. These statistics account for variation within localities across time. For example, if a new high school opens, a town may switch from having one high school

[5]The data used in this study were obtained mainly from Diana Coman (Coman, 2020), who hosts a data repository with scraped records from the high school admissions and graduation websites hosted by the Romanian Education Ministry.

[6]Students may be unmatched for several reasons. Some schools offer admissions using different criteria than the admission exam (for example, art schools), while students in other schools do not write the graduation exam. Students may also drop out, so, in this sense, the results are subject to sample selection. This issue is addressed via a Heckman two-stage estimation. Lastly, students may switch schools and have very common names, which makes it difficult to match them accurately. More notes on matching are available in Appendix B.

to two high schools.

Generally speaking, the schools in one-high school towns are smaller than those in towns with more high schools. However, class sizes are typically fixed at around 28 students, so class size will not vary with town size (except in heavily undersubscribed schools). At the same time, high school admission scores, graduation scores and teacher test scores are increasing in the number of high schools in a town, which probably captures socioeconomic differences between rural and urban areas. Schools typically offer the same number of tracks and hire the same amount of new teachers regardless of town size, except for towns with more than 16 high schools, where more teachers per school are hired. Lastly, schools spend more money per capita in places with many high schools, but this is mainly driven by large contract items, such as renovations. Spending on everyday items is similar across the different considered categories.

3 School Choice, Student Sorting and Achievement Gaps

Sorting In this section, I present two motivating findings. I first show how more school choice leads to dramatic increases in student sorting and, second, that those student sorting patterns are mirrored by increases in student test score inequalities.

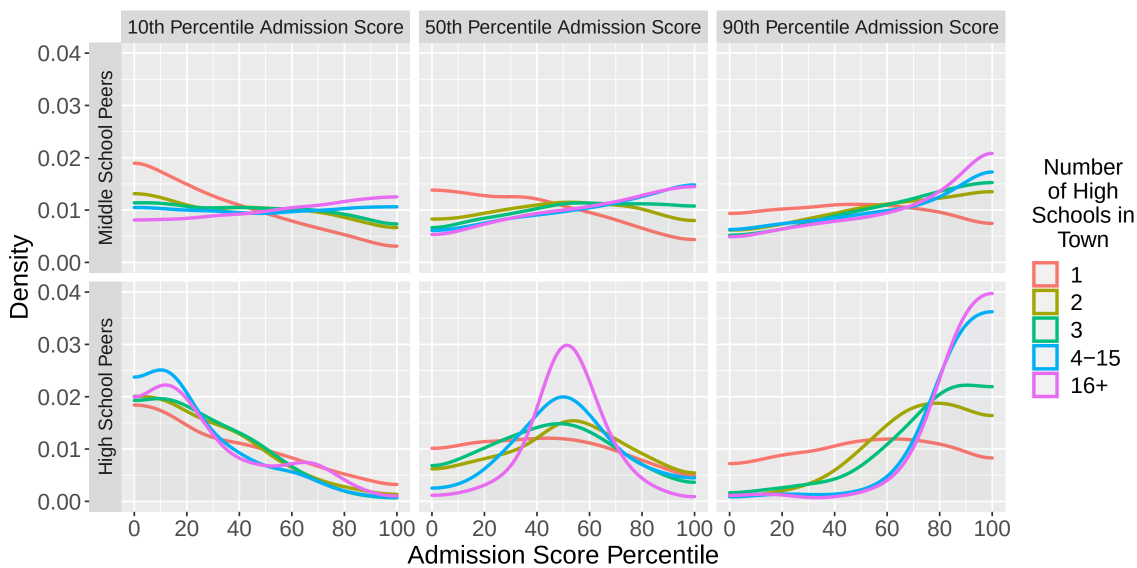

Figure 1: This figure shows peer ability varies with own admission score and with the number of high schools in the town, at the end of middle school and the beginning of high school. Peers are defined as students who attend the same school-cohort. Each panel shows distributions of peer high school admission scores for a given own admission score. The top panels show middle school peer distributions and the bottom panels show high school peer distributions.

Figure 1 illustrates student sorting patterns by high school admission score at the end of middle school and the beginning of high school. The most striking pattern is that i) the reshuffling of students between the end of middle school and the beginning of high school leads to a dramatic increase in sorting across admission scores and ii) this sorting is much more pronounced in localities with many high schools.

Indeed, across middle schools (top panels), conditional on the number of high schools in a town, student sorting is limited. In other words, the peer composition of students with low admission scores (top left panel) is very similar to that of students with high admission scores (top right panel). As I discuss in a later section, middle schools in Romania are assigned based on proximity and geographic sorting by socioeconomic characteristics is relatively weak, with sorting patterns still heavily influenced by the largely egalitarian housing assignment of the communist regime.

Across high schools (bottom panels), sorting is much more pronounced. First, across towns with similar numbers of high schools, students with high admission scores (bottom right) sort into high schools where their peers tend to have high admission scores. In contrast, students with low admission scores (bottom left) are relegated to schools with much lower-scoring peers.

Second and crucially, these sorting patterns are much more pronounced in locations with many high schools than in those with few. Indeed, a high-scoring student in a town with more than sixteen high schools (bottom right) will attend high school almost exclusively with high-scoring peers, while a similar student in a one-high school town will have schoolmates with wildly varying admission scores.[7]

These sorting patterns are a result of the competitive nature of the admission process and reflect student preferences over certain schools. Note that by looking at the sorting patterns, one cannot distinguish between student preferences over peer groups, student preferences over high-value added schools or a combination of both or other factors. For the remainder of the paper, I use the average admission score of students admitted to schools/tracks as a measure of school selectivity or desirability, without taking a stand on the exact process by which students choose schools. Ainsworth et al. (2020) provide evidence that in Romania students tend to sort into high-value-added schools, although imperfectly, with some value-added being "left on the table". That being the case, school choice enables high-scoring students to choose high-value added schools and may positively impact their learning outcomes, while low-scoring students are relegated to low-value added schools, attended by progressively lower-scoring peers.

Student Achievement Gaps In Figure 2, I now show that the achievement gaps in graduation scores are consistent with the student sorting patterns across admission scores.

First, low-scoring students score higher on the graduation exam when they attend high school in locations with fewer high schools, where there is less potential for sorting, making them less likely to be relegated to poor-quality high schools. More specifically, students with admission scores in the lowest (national) decile score 0.1 (2.8) percentiles higher than students in towns with two (sixteen and more) high schools.

Second, at the other end of the admission score distribution, high-admission score students perform progressively better on the graduation exam when attending high school in towns with more high schools, where they can sort into more selective schools. Indeed, compared to students in one-high school towns, students with admission scores ranked in the top decile score, on average 0.8 (2.9) percentiles higher on the national graduation exam when there are two (sixteen or more) high schools in their town. Together, these findings suggest that graduation score gaps widen in localities where students can more heavily sort by test scores across schools.

In the remainder of the paper, I establish a causal link between the number of school choices students have and increasing inequalities in educational outcomes. First, having just shown that student sorting patterns shift strongly with the number of high schools, I will show that there are plausible reasons why the number of high schools across towns with similar populations varies exogenously. Then, I will exploit this exogenous variation in the number of high schools

[7]Figure 5 shows similar sorting patterns for high school-track peers, which are even more pronounced.

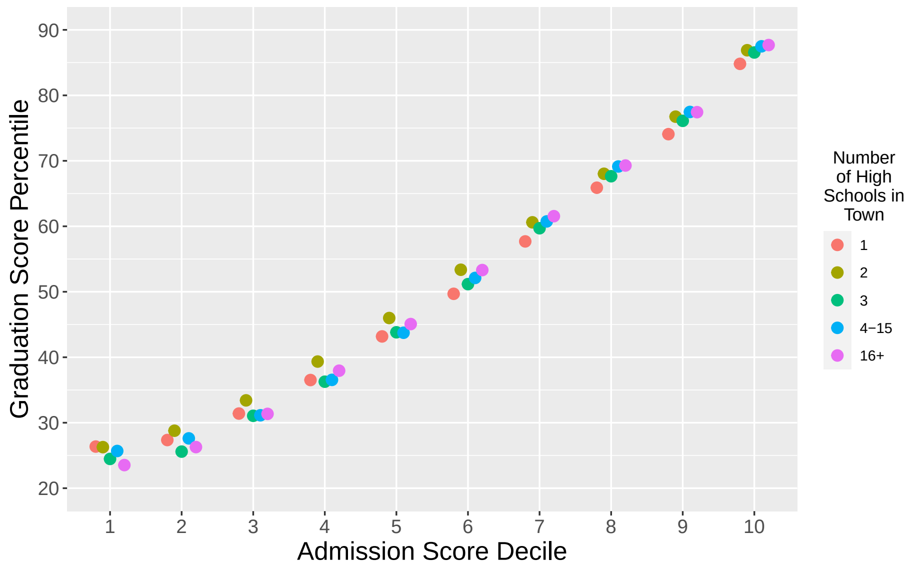

Figure 2: This figure shows how mean graduation exam scores vary with admission scores and with the number of high schools in the town of high school attendance, for all students graduation between 2008 and 2019. Standard deviations are too small to feature on the graph.

across locations to tease out differences in student sorting and, ultimately, in student learning outcomes.

4 Identification

4.1 Quasi-Random Variation in the Number of High Schools

I now argue that differences in the number of high schools across locations with similar student populations are quasi-random. Several arguments underlie this claim. First, baseline student characteristics across towns with similar populations but different numbers of schools are similar. Second, Romanian households are relatively geographically immobile and not strongly sorted by socioeconomic characteristics within towns or across similar towns due to the communist legacy. Lastly, the number of schools has essentially been frozen since the 1970s, even though significant demographic and economic changes have impacted different regions differently, especially since the fall of the communist regime in 1989. Together, these suggest that the variation in the number of high schools across towns with similar characteristics is largely orthogonal to contemporaneous differences in student characteristics across these locations.

1. Baseline student characteristics: High school student admission score distributions in towns with similar student populations but different numbers of high schools are not statistically different. Table 2 shows this. The top panel shows differences in student admission scores between 1- and 2-high school towns whose student populations in a given year fall in the same 50-admitted student bin. Both the average admission score and the distribution of admission scores are statistically indistinguishable from each other. I generalize this to all $n-1$ and n high school towns that fall in the same 50-admitted student bin in a given year. Again, student admission scores are not statistically different between these two types of towns.

Table 2: Student Characteristics in Towns with Similar Populations and Different Numbers of High Schools

2 vs 1 High School Towns	1 HS	2 HS	Δ	p-value
Mean Admission Score Percentile (0-100)	40.32	39.81	-0.51	0.41
Proportion of Quartile 1 Admission Scores (%)	35.23	36.16	0.93	0.35
Proportion of Quartile 2 Admission Scores (%)	29.15	29.34	0.19	0.81
Proportion of Quartile 3 Admission Scores (%)	22.64	20.78	-1.87	0.14
Proportion of Quartile 4 Admission Scores (%)	12.98	13.73	0.75	0.95
Towns per Bin	140.60	168.60		
n vs n-1 High School Towns	**n-1 HS**	**n HS**	**Δ**	**p-value**
Mean Admission Score Percentile (0-100)	51.53	51.01	-0.52	0.63
Proportion of Quartile 1 Admission Scores (%)	22.65	23.04	0.38	0.91
Proportion of Quartile 2 Admission Scores (%)	24.99	25.42	0.43	0.22
Proportion of Quartile 3 Admission Scores (%)	26.36	26.16	-0.20	0.43
Proportion of Quartile 4 Admission Scores (%)	26.00	25.38	-0.62	0.66
Towns per Bin	45.51	45.40		

The top panel shows comparisons of student characteristics between one- and two-high school towns with similar student populations (i.e. total yearly student enrolments that fall into the same 50-student bins). The bottom panel generalizes this to include similar-total enrolment towns with any n-1 and n high schools.

2. Romanian household (im)mobility. Romanian households are relatively geographically immobile, making it unlikely that households sort across locations to attend better schools. A particular institutional and historic context engenders this reality. Using the Romanian 2011 census, I show that only 11% of Romanian enrolled high school-aged children lived in a locality that was neither their parents' birthplace nor their place of residence in 1990. Indeed, before the fall of the communist regime in 1989, individuals entering the labor market were assigned jobs across the country based on their qualifications and centrally-determined labor demand. Also, since the private property of land or homes was essentially abolished, housing was assigned quasi-randomly based on availability. At the fall of the communist regime, households were allowed to purchase the homes they were occupying and were given access to mortgages. Due to rampant hyperinflation in the early 1990s, most households could then quickly pay off these mortgages. At the same time, relatively weak economic conditions in the post-communist economic recovery made for a relatively thin real estate market. Today, Romania continues to boast the highest homeownership rate in the world (96.4% in 2018).[8] At the same time, household wealth inequality in Romania is very low, with a household wealth GINI ranked among the lowest in the world.[9] As a result, while a strong urban-rural sorting exists in Romania, Romanian households today continue to be weakly geographically sorted by socioeconomic characteristics across similar towns.

3. High school numbers across localities: The number of high schools across Romanian towns is predetermined and largely divorced from town socioeconomic conditions in the sample period. In Table 9 of the appendix, I show several pieces of evidence in this regard. Roughly 95%

[8]According to Eurostat (2021).
[9]According to Group (2019).

of the variation in the number of high schools across towns is explained by the town population measured immediately after the fall of the communist regime in the 1992 census.

Second, local changes in population, average wages and unemployment between 1992 and the sample period do not predict changes in the number of high schools. Indeed, between 1992 and 2019, the last year of the sample, the Romanian population has officially decreased by 15%.[10] Moreover, the post-communist period in Romania has seen a host of economic changes across towns. Small towns, in particular, which were often centered around one state-owned enterprise, have seen significant changes in their fortunes as many of those enterprises have seen layoffs, privatization, or shut down altogether. Nonetheless, the changes in high school numbers across towns are minimal.

Lastly, although I lack the data to confirm this, the number of high schools across towns was probably determined even earlier, in the 1960s. The Romanian high school expansion essentially ended at the beginning of 1970s, after the visit of dictator Nicolae Ceausescu to The People's Republic of China and DPR Korea. The number of high schools and university graduates was reduced to ensure a higher supply of manual laborers and reduce political dissent. The decades preceding the fall of the regime were punctuated by severe recessions in the context the Oil and Energy Crises. They were exacerbated by a policy of austerity whose aim was to eliminate foreign government debt. In this climate, expansions in upper-secondary and tertiary education were halted. Meanwhile, in post-1989 Romania, the generally good school coverage, lack of funding and a rapidly decreasing school-age population made school openings a rarity.

4.2 Instrumental Variable Approach

Having argued that the number of schools across locations with similar student populations is quasi-random, I now use this variation as an instrument shifting the type of schools students attend. Specifically, I first use the number of high schools in a student's town, interacted with their admission score, as a shifter of how selective a school a student will be able to attend, conditional on student and town baseline characteristics. Each high school's selectivity will be proxied by its average admission score, which leads to the following first stage equation:

$$\mu^{e}_{-iht} = \gamma_0 + \beta_e e_i + \gamma_X X_{ct} + \delta_d + \delta_n + \beta_{d\times X} d_i \times X_{ct} + \delta_m + \delta_{d\times n} + \delta_c + \delta_t + \epsilon_{icmht} \tag{1}$$

Here, μ_{-iht} is the mean admission score in high school h and year t (excluding student i), X_{ct} is a matrix of town characteristics, including unemployment rate, high school dropout rate, average wage at the county level and the size of the high school entering cohort at time t, δ_d is an admission score decile fixed effect,[11] δ_n is a fixed effect corresponding to the number of high schools in a town, $d_i \times X_{ct}$ is an interaction between student admission score decile and town characteristics that captures differences in student sorting for students with comparable admission scores, but living in towns with different characteristics, $\delta_{d\times n}$ is a series of fixed effects capturing the interaction between the number of high schools in a given town and a student's admission score decile. This allows the model to capture differences in student sorting across the admission score distribution and across towns with varying numbers of high schools. Lastly, δ_m, δ_c and δ_t are middle school, town (city) and year times effects, respectively.

In the second stage, I use the variation in student sorting engendered by the differences in the numbers of schools across similar locations to estimate the effect of school choice (and

[10] Although estimates suggest that the population decrease is much higher, with many people de facto residing in the European Union, while maintaining a legal residence in Romania.

[11] At the town-cohort level, capturing the student's within-town and cohort admission score rank.

sorting) on student outcomes at the high school graduation exam. The second stage equation is:

$$g_i = \beta_0 + \beta_e e_i + \beta_X X_{ct} + \delta_d + \delta_n + \beta_{d\times X} d_i \times X_{ct} + \delta_m + \hat{\mu}^e_{-iht} + \delta_c + \delta_t + \epsilon_{icmht} \quad (2)$$

Here, g_i is the graduation score grade of student i who entered high school h in year t from middle school m in town or city c and $\hat{\mu}^e_{-iht}$ is the first stage estimate.

It is important to keep in mind that μ_{-iht}, the average peer admission score, should be interpreted as a measure of school selectivity, rather than something that will help capture peer effects. This school selectivity parameter is correlated with value-added Ainsworth et al. (2020), which may be driven by peer effects, teacher characteristics, school resources or efficiency of school management. In this sense, the model captures how school choice enables high-ability students to sort into more selective schools and how, in turn, this affects their graduation score.

4.3 Triple Difference Approach (School Openings)

To validate the results in the previous section, I exploit school openings. A high school opening in a town with few high schools is an event that disrupts preexisting sorting patterns. For example, in a town with only one high school, all high school students must attend it unless they choose to migrate, which is costly. If a second high school opens, students will now compete for admission into their most preferred high school. Thus, high school openings create more school choice and competition, disrupt preexisting sorting patterns, and may affect student achievement through this channel.

As I previously argued, school openings are virtually absent in Romania. There are only three high school openings in my twelve-year sample across the more than three hundred one- and two-high school towns. I study these three openings in a triple difference framework that contrasts the graduation grades of:

1. high- versus low-admission score students across
2. treatment towns (where a new high school opens) and control towns (which are similar in size, but where no new high school opens)
3. before the high school opening versus after the high school opening

I estimate the following model, which will capture how the graduation exam score gap between high- and low- achieving students is impacted by a high school opening:

$$g_i = \beta_0 + \beta_e e_i + \beta_X X_{ct} + \beta_{q\times X} q_t \times X_{ct} + \beta_T \mathrm{T}_{ct} + \delta_q + \delta_c + \delta_t + \delta_{qt} + \delta_{qc} + \delta_{Tq} + \epsilon_i \quad (3)$$

Here, g_i is the graduation score grade of student i who entered high school h in year t from middle school m in town or city c, X_{ct} is a matrix of town characteristics, including unemployment rate, high school dropout rate, average wage at the county level and the size of the high school entering cohort at time t, δ_q is an admission score quartile fixed effect,[12] δ_c and δ_t are town (city) and year times effects, respectively and δ_{qt}, δ_{qc} are fixed effects representing the interaction of a student's admission score quartile and year and town dummies, respectively. Lastly, T is a treatment indicator which takes the value of 1 only for cohorts entering high school at the time or after the opening of a new high school in their town. Tq captures interaction effects between the treatment dummy and students in different quartiles of the admission score distribution,

[12]Where admission score quartiles are computed at the town-cohort level.

thus allowing the model to capture differences in the impact of a school opening across admission grades.

The identifying assumption is that the timing of a high school opening in a given town is orthogonal to the change of the graduation score gap between high- and low-admission score students over time. In other words, the decision to open a new high school in a town and its precise timing is not correlated with an expected change in the relative performances of high- and low- entrance score students. I believe that this assumption is very plausible. Given that between the decision to consider opening a new school, approving the opening, earmarking the necessary funds, constructing the school, staffing it and finally opening it, a long period of time probably elapses. The following section demonstrates that a school opening immediately impacts town-level student sorting and student grades of the first entering cohort exposed to the opening. The opening itself plausibly causes these effects and not other confounding factors.

5 Results

5.1 Instrumental Variable

5.1.1 School Choice and Sorting

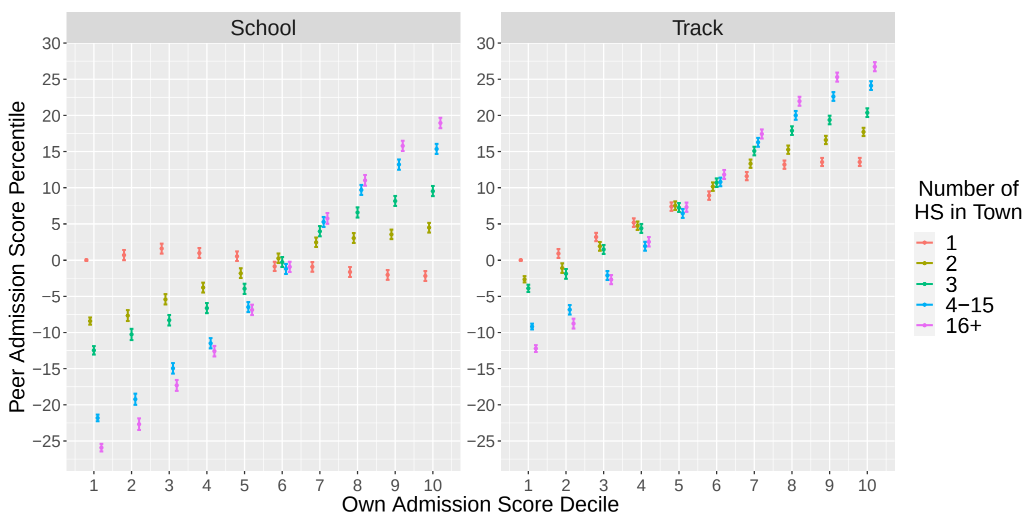

Figure 3: This figure plots the expected mean admission score of a student's peers conditional on his or her entrance grade and number of high schools in the town of high school attendance, from equation 1. The left panel shows peer admission scores in the student's high school cohort. the right panel shows peer admission scores in the student's high school track cohort.

The effect of school choice on student sorting patterns (presented in Figure 3 in this text and in Tables 10 in the Appendix)[13] suggests that sorting intensity across schools and tracks is increasing rapidly in the number of high schools in a town, even when controlling for student population and other town characteristics.

First, within-town sorting is increasing in the number of high schools. In the left panel of Figure 3, sorting by admission scores is so severe in towns with sixteen high schools or more

[13]Both Wu-Hausman tests for endogeneity and weak-instrument F-tests have p-values of 0, for both school- and track-level regressions.

that lowest-decile students are admitted to schools with 45 percentiles lower average admission scores than their top-decile counterparts. In towns with one high school, sorting across schools is non-existent, as all students attend the same high school unless they are willing to migrate.[14] Sorting across tracks (in the right panel of Figure 3) is significant across tracks even in one high school towns. Top-decile students attend tracks with 14 percentile higher average admission scores than their lowest-decile counterparts. However, this effect is more pronounced in many-high school towns, where this gap stands at 39 percentiles.

Significant sorting differences emerge when comparing students with similar admission scores across towns with different numbers of high schools. Top-decile students in many-high school towns attend schools (tracks) with 21 (11) percentile higher admission scores than their counterparts in one-high school towns. At the other end of the admission score distribution, lowest-decile students in towns with more than sixteen high schools are relegated to schools (tracks) where the admission scores are 26 (12) percentiles lower than their counterparts in one-high school towns, who benefit from the absence of sorting in their towns.

5.1.2 School Choice and Student Scores

Finally, I explore the effects of school choice on student outcomes across the admission score distribution.

Table 3: Effect of Attending a More Selective School (Stage 2 IV)

	Graduation Score Percentile				
	School Level		Track Level		Tide
	OLS	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)	(5)
Admission Score (e_i)	0.539***	0.526***	0.512***	0.458***	0.590***
Peer Admission Score (μ_{-i})	0.140***	0.177***	0.214***	0.364***	
2 HS-Town					−0.005
3 HS-Town					−0.027**
4-15 HS-Town					−0.015
16+ HS-Town					−0.027
Observations	1,161,358	1,161,358	1,161,135	1,161,135	1,161,358
Adjusted R^2	0.64	0.64	0.64	0.64	0.64

This table shows how graduations cores vary across towns with different numbers of high schools. Columns (1) and (3) show OLS regressions of graduation scores on admission scores and school-cohort and track-cohort admission scores respectively. Columns (2) and (4) instrument peer admission scores using an interaction between the within-town student admission score decile and the number of high schools in the town (as per equation 2). Column (5) shows regressions highlights differences in graduation scores conditional on admission scores, across towns with different numbers of high schools. Controls include within town-cohort own admission score decile and interactions of these decile dummies with: the number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data). Additional controls include the number of high schools in town (grouped into 4 bins), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.

First, in Table 3, I show that sorting into a school (track) with one percentile higher average

[14] Migration across towns is addressed in a later section.

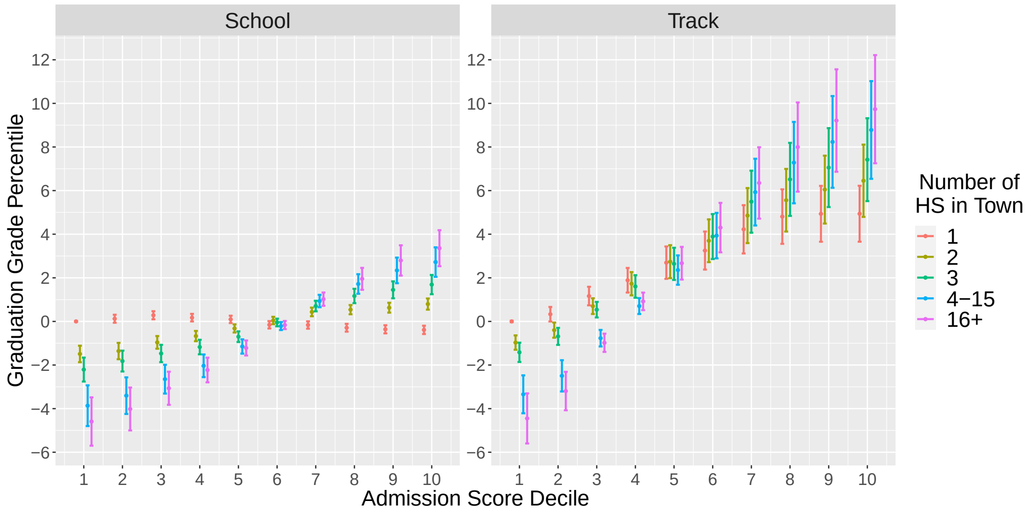

Figure 4: This figure plots the expected mean causal effect of sorting on graduation grades, by entrance grades and number of high schools in the town of high school attendance.

admission scores, conditional on own and town characteristics, causes a 0.18 (0.36) percentile increase in the graduation score. These results are consistent with Pop-Eleches and Urquiola (2013), who find improvements in the scores of students who are marginally able to sort into more selective schools.[15] Column (5) of this table also shows that conditional on town and student characteristics, there is no difference in graduation scores across towns with different numbers of schools. Thus, no evidence suggests that school choice acts as a "tide that lifts all boats" by encouraging competition across schools.

Then, in Figure 4, I show how these effects stack up across the admission score distribution to create a widening in academic achievement gaps. I plot the average effect of school choice on graduation scores by student admission scores and the number of high schools in their town. School choice, through sorting, exacerbates inequalities in educational outcomes. Indeed, sorting across schools (tracks) first widens the graduation score gaps between high- and low-admission score students in towns with more than sixteen high schools by almost 8 (14) percentiles. Second, it widens graduation score gaps between high-admission scores students in places with many high schools. The latter can sort into very selective schools and outperform comparable students in places with only one high school by 4 (5) percentiles. Third, an additional 5 (4) percentile graduation score gap forms between low-admission score students in places with many high schools, who are relegated to low-quality schools and comparable students in towns with only one high school.

5.2 Other Outcomes

I now explore several other outcomes. First, the probability of matching a student's admission and graduation records. Inability to match indicates dropping out, changing schools and being unable to match the student due to a common name or the student not registering for the exit exam. Second, the probability of changing schools. Third, the probability of passing the exit

[15] As a technical point, F-statistics for a weak instrument test are computed for the first stages as per Sanderson and Windmeijer (2016). All F-statistics are sufficiently large to rule out weak instruments.

exam conditional on registering for it. And fourth, the probability of registering for the exit exam and not showing up to write it.

Results are presented in Table 4. The match rate (which is a proxy for the high school dropout rate) between admission and graduation records is higher for students who sort into more selective schools, while the probability of switching schools is lower. Sorting into a school with one percentile higher school (track) admission score results in a 0.28 (0.42) percent higher match rate and a 0.29 (0.67) percent lower school switching rate. However, sorting into a more selective school (track), conditional on admission scores, is related to a lower exit exam pass rate, which is mainly driven by higher absenteeism. Indeed, attending a one percentile higher admission score school results in a -0.1 (-0.31) percent lower probability of passing the exit exam and a 0.13 (0.29) higher probability of being absent from the exit exam (conditional on registering for it). One possible explanation for this result is that ceteris paribus, marginal students from more selective schools are more likely to register for the exit exam and not attend it.

Table 4: Other Outcomes

	Matched	School Change	Pass Exit Exam	Exit Exam Absence
Own Admission Score	0.728***	−0.027	0.647***	−0.112***
Peer Score (School)	0.282***	−0.301***	−0.094	0.135***
Observations	2,166,575	1,341,775	1,341,775	1,341,775
R^2	0.50	0.19	0.41	0.12
Wu-Hausman p-value	0	0	0	0
Own Admission Score	0.603***	0.103***	0.715***	−0.167***
Peer Score (Track)	0.425***	−0.680***	−0.292**	0.294***
Observations	2,165,841	1,341,062	1,341,062	1,341,062
R^2	0.55	0.16	0.41	0.10
Wu-Hausman p-value	0	0	0	0

This table shows second stage results from a 2SLS least square regression of several outcomes: 1) admission-graduation match rate (a proxy of dropout rate), 2) change of school rate, 3) exit exam pass rate and 4) exit exam absenteeism rate. The endogenous variable is students' mean peer admission scores (instrumented by student's own admission rank and number of high schools in their town). The top panel shows results from separate regressions using high school peers and the bottom panel shows results from regressions using track-level peers. Controls include within town-cohort own admission score decile and interactions of these decile dummies with: the number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data). Additional controls include the number of high schools in town (grouped into 4 bins), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.

5.2.1 Robustness Checks

Migration I conduct three robustness checks to validate the results. First, migration across towns can bias the results. In particular, there is potential selection on unobservables. For example, more motivated students may disproportionately apply to high schools in locations with higher student sorting, where they can attend a more selective school. To the extent that these unobservables (rather than attending a more selective school) affect performance, the above estimates are upward biased.

I address this issue in Appendix C.1. Instead of using towns as separate educational markets, I define these markets endogenously. For example, if sufficiently many students from other middle schools in town A enroll in high schools in both town A and B, then both towns A and B will be considered part of the same market. Using this approach, I reestimate the first and second stages of the instrumental variable model at the school and town levels. I additionally exclude cross-market migrants from the analysis. The second stage results are presented in Tables 17 to 20 of the Appendix C.1. The results are very robust to these different specifications.

Sample Selection Second, there is a possible sample selection issue: I can only observe the graduation grades of students who write the graduation exam and not those who drop out of high school. I use a Heckman two-stage correction for models with endogenous variables to address this. The idea behind this approach is to use an instrument that, conditional on other covariates, can predict a student's probability of dropping out without directly affecting their grades. I use the proportion of high school dropouts in a student's middle school peers. The intuition is that this instrument does not affect high school performance conditional on entrance grade. Still, observing middle school peers dropping out may dissuade a student (or their parents) from exerting extra effort to keep the child in high school. Although there is some evidence of sample selection, the results adjusted for sample selection are qualitatively similar to the unadjusted ones. For more details, consult Appendix C.2.

First Stage Overidentification Lastly, I address a first stage overidentification concern. Indeed, there are 36 instruments (4 high schools/town dummies and 9 decile dummies) used in the first stage for only one endogenous regressor. The Sargan-Hansen overidentification test does indeed yield a p-value close to 0. Although this is not necessarily a concern, given the large sample size and precise estimates,[16] I reestimate the IV model using only 2 instruments: an indicator of above/below median admission score and an indicator of a town with more than 3 high schools. I present the results in Appendix C.3. This alternative specification yields very similar results to those shown above, while producing an insignificant Sragan-Hansen statistic.

5.3 School Openings: Triple Difference

Table 5 shows the effects of school openings on student outcomes. Using high school openings in one- and two-high school towns, I first show in column 1 that high school openings exacerbate student sorting by admission scores across schools. After a new high school opens, above-median admission score students sort into high schools attended by peers with 5 to 6 percentiles higher admission scores.

Next, in column 2, I show that after a new high school opens in a town, the average achievement of students, conditional on their admission scores, does not improve. Therefore, there is

[16] As Angrist and Pischke (2008) point out: "In our experience, the over-ID statistic is often of little value in applied work. Because [the Sargan-Hansen test] measures variance-normalized goodness of fit, the over-ID test-statistic tends to be low when the underlying estimates are imprecise. [...] On the other hand, in cases where the underlying IV estimates are quite precise, the fact that the over-ID statistic rejects need not point to an identification failure."

Table 5: Effect of School Openings on Student Graduation Scores

	Peer Admission Score	Graduation Score	
	(1)	(2)	(3)
Admission Score	0.22***	0.66***	0.63***
Post × Treated	−2.1	−4.9	−1.2**
Q2 × Post × Treated	0.1		6.0***
Q3 × Post × Treated	5.1**		11.0***
Q4 × Post × Treated	6.0*		8.2**
N	219,338	211,528	211,528
R^2	0.74	0.56	0.58

This table shows the impact of high school openings on student sorting (1), mean graduation scores (1) and the distribution of graduation scores (3). Data includes all one- and two-high school towns. I exclude towns where a non-general (e.g. religious denominational or private) high school opens. Admission and graduation scores are in national-cohort percentile ranks, quartiles (Q) are town-cohort admission score quartiles. All variables are interacted with the number of high schools in a town at baseline. I include year and town fixed effects and control for county high school dropout rates, unemployment rates, average wage rates and high school track type. For models (2) and (3), I interact the additional controls with the admission score quartiles (Q) to capture differences in the way students with different abilities perform in areas with different characteristics. Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the town level.

little evidence to support the claim that school choice is a "tide that lifts all boats" by fostering inter-school competition.

Lastly, in column 3, I show that the additional sorting engendered by new schools opening in small towns leads to an increase in score gaps at the end of high school. Students in the lowest admission score quartile, who are relegated to less elective schools, score 1.2 percentiles lower after a new school opens in their town. Meanwhile, third- and fourth-admission score quartile students score 11 and 8.2 percentiles higher, respectively, as they are able to sort away from low-achieving students and attend high schools with higher-scoring peers. Moreover, a new high school opening potentially causes a reallocation of teachers and other resources across schools in ways that can exacerbate inequalities in access to quality education across admission scores.

6 Decomposing Sorting Effects

This section analyzes three possible channels through which student sorting plausibly impacts grades. I provide descriptive evidence on the importance of peer effects, teacher ability and school spending channels on student outcomes at graduation.

6.1 Peer Effects

School choice can affect student grades via peer effects. As school choice increases student sorting, high-admission score students are exposed to increasingly higher-ability peers in their high schools. Meanwhile, low-admission score students are exposed to progressively lower-ability peers as school choice-generated sorting increases. If peers exert influence on one another, this is a channel by which school choice can further exacerbate graduation gaps between high- and

Table 6: Peer Effects

	Graduation Score (OLS)	Graduation Score (IV)
Admission Score	0.46***	0.39***
Change in Mean Track Admission Score	0.06***	0.12***
Mean Track Admission Score	0.23***	0.40***
Observations	507,692	507,692
R^2	0.65	0.65

This table shows how cohort-to-cohort changes in peer admission scores correlate with graduation scores. Controls include within town-cohort own admission score decile and interactions of these decile dummies with: the number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data). Additional controls include the number of high schools in town (grouped into 4 bins), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the town level.

low-scoring students.

I identify peer effects using variation in admission scores of students admitted to the same tracks across different years. Since high school and track rankings are very stable over time in Romania, this variation is generated by random variation in admission scores across cohorts. I restrict my attention to tracks with fewer than 25 students, where all admitted students are guaranteed to be placed in the same classroom. I do this in order to circumvent the issue of classroom allocation, which is often non-random in Romanian high schools.

Table 6 shows that, conditional on town, school, track and individual controls, being admitted to a given track in year where peer admission scores are 1 percentile higher is associated with a 0.12 percentile increase in student graduation scores. The results suggest that peer effects drive roughly one-third of the effects of sorting into a better track.

6.2 Teacher Ability

Table 7: Teacher Sorting

Number of High Schools in Town	1	2	3	4-15	16+
Average Teacher Score (Percentile)	47	47	49	49	54
Teacher Score-Student Admission Score Correlation	0.14	0.17	0.10	0.26	0.31

This table shows the average teacher placement score (row 1) and the within-school correlation between teacher placement scores and student average admission scores (row 2) by towns with different numbers of high schools.

Access to high-ability teachers is another important channel through which school choice-driven student sorting may impact their outcomes. In particular, if high-achieving students, who have school choice priority over low-achieving students, can sort into schools with more capable teachers, this can further enhance their learning and improve their outcomes at graduation. In the following paragraphs, I first show that high-admission score high schools disproportionately hire teachers who achieve high grades on their placement exams and that this effect is more pronounced in places with many high schools. Second, I show that teacher placement scores, conditional on student and school characteristics, strongly predict student graduation scores, much more so than teacher experience, certifications or college GPA. Third, I show evidence that high-scoring students benefit more from being taught by high-placement score teachers than low-scoring students.

Teacher sorting patterns display three main trends, summarized in Table 7. First, high-score teachers are more likely to work in towns with more high schools. Teachers in locations with more than sixteen high schools score, on average, 7 percentiles higher on the placement exams than those in one-high school towns. Second, high-placement score teachers sort into schools attended by high-admission score students. Indeed, there is a positive correlation between teacher placement and student admission scores across high schools. Third, high-score teachers sorting into high-admission score high schools is more pronounced in locations with more high schools. Putting all this evidence together suggests that high-admission score students are more likely to be taught by high-placement score teachers and that this effect is larger in places with many high schools.

Next, I show that conditional on student and school characteristics, teacher placement scores are strongly predictive of student graduation exam scores. In column 1 of Table 8, I find that a one percentile increase in the average student placements scores is associated with a 0.08 percentile increase in student graduation scores, conditional on student admission scores and high school fixed effects as well as other school and town characteristics. Placement exam scores predict graduation exam scores much more strongly than other measures of teacher ability, such as college GPA, education level, teaching experience or teacher certifications.[17] Column 2 shows that being exposed to high-scoring teachers yields higher graduation scores particularly in science and math-intensive fields. A percentile increase in the average teacher scores yields large increases in graduation scores in the chemistry (0.13 percentiles), computer science (0.25), economics (0.21) and physics (0.20) elective components of the graduation exam.

6.3 School Spending

Next, I document the potential link between school spending patterns and student achievement. High-admission score students may use school choice to sort into schools with more material resources. To the extent that these resources are used to impact student learning positively, this can be a channel through which school choice can lead to higher inequalities in educational outcomes. Because school spending does not impact student test scores, I restrict myself to summarizing the empirical findings regarding spending. More details are available in Appendix A.6.

First, school spending per student is higher in schools with low-admission score students. Figure 6 of the appendix shows that both at the national level and within-towns, high-admission score students attend schools with lower per-student yearly spending. There are three plausible explanations for this: low-admission score schools have lower (unobserved) stock of infrastructure and need extra expenditure to be brought up to level, high-admission score schools are larger and more urban on average and require less spending per student due to economies of

[17] A limitation is that teacher value-added cannot be measured directly, as I do not observe teacher classroom assignment. Moreover, I only observe teachers hired in the 2015-2019 period. I use the average placement score of teachers, weighed by the number of weekly hours each teacher was hired to teach, to construct an index of teacher ability for each student.

Table 8: Teacher Placement Scores vs Student Graduation Scores

	Graduation Score	
	1	2
Own Admission Score (Romanian)	0.351***	0.352***
Own Admission Score (Math)	0.332***	0.334***
Teacher Placement Score	0.078***	0.015
Teacher College GPA	−0.011*	−0.011*
Teacher Experience (Years)	−0.001***	−0.001***
Teacher Rank	0.002	0.003
Teacher Education	−0.005	−0.003
Mean Peer Admission Score	0.118***	0.116***
Teacher Placement Score × Chemistry		0.110***
Teacher Placement Score × Computer Science		0.237***
Teacher Placement Score × Economics		0.197***
Teacher Placement Score × Geography		0.018
Teacher Placement Score × Other Elective		0.057***
Teacher Placement Score × Philosophy		0.005
Teacher Placement Score × Physics		0.188***
Teacher Placement Score × Psychology		0.013
Observations	519,301	519,301
Adjusted R^2	0.51	0.51

This table shows results from a regression of student graduation scores on student admission score components and average characteristics of teachers employed in their high school. These characteristics include teacher placement exam scores (in national percentile), college GPA, experience in years, rank (i.e. whether or not the teacher passed rank exams, which come with a pay increase) and teacher education level. Additional controls include track type, year fixed effects, towns fixed effects and middle school fixed effects. Sample includes students attending a high school and track where at least one teacher was hired during the 2015-2019 period. The reference level in model 2 is biology. Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the town level.

scale and, lastly, that the government is willing to spend more money on schools with low-achieving students, who tend to come from disadvantaged backgrounds, to narrow the learning gap between them and more privileged students.

Second, there is no evidence that differences in school spending translate into better student outcomes. Table 15 in the appendix shows that, conditional on student admission scores and controls for numbers of high schools in a town, school spending does not predict student graduation scores well. One limitation is that the stock of material resources available to a school is unobserved. As noted previously, spending flows might occur due to a deficit in school resources. In that sense, spending provides an imperfect measure of resources available to schools.

7 Discussion and Conclusion

This paper investigates the effects of school choice on student sorting and their educational outcomes, using administrative data from Romanian high schools, generating two main findings. First, school choice coupled with competitive admissions can lead to severe student sorting on test scores. This type of sorting is much higher than the one generated by neighborhood assignment rules. Moreover, the more schools students have to choose from, the more pronounced the sorting.

Second, this sorting increases the test score gaps between high- and low-ability students without affecting mean achievement. Therefore, school choice is not a “tide that lifts all boats”. Instead, it mainly exacerbates inequalities in access to good schools. In large cities, where students have many schools to choose from, school choice-induced sorting is severe and it widens the inequalities between high- and low-admission score students by roughly 8 percentiles. When considering sorting across tracks within schools and sorting across schools, this figure stands at 14 percentiles. School openings in small towns confirm these findings: a new school opening in a town with only one or two high schools leads to a widening score gap between high- and low-achieving students by an average of 9 percentiles.

The two main channels underlying the widening of these score gaps are peer effects and access to high ability teachers. When high-admission score student are able to sort into more selective schools, they are exposed to better teachers and other high-scoring pupils, which helps their academic performance.

In conclusion, the Romanian high school system, which combines school choice with exam-based admissions, serves as a cautionary tale. Unless policymakers ensure that students have equitable access to good (or selective) schools, the efficiency gains from school choice can easily be dwarfed by the increase in score dispersion, with the most vulnerable students emerging as losers. This effect is especially stark if students (or their parents) have preferences over peers, which will mechanically induce students to sort across schools without schools having to necessarily improve the quality of their services.

Appendices

A Additional Tables, Figures and Regression Results

A.1 Student Sorting

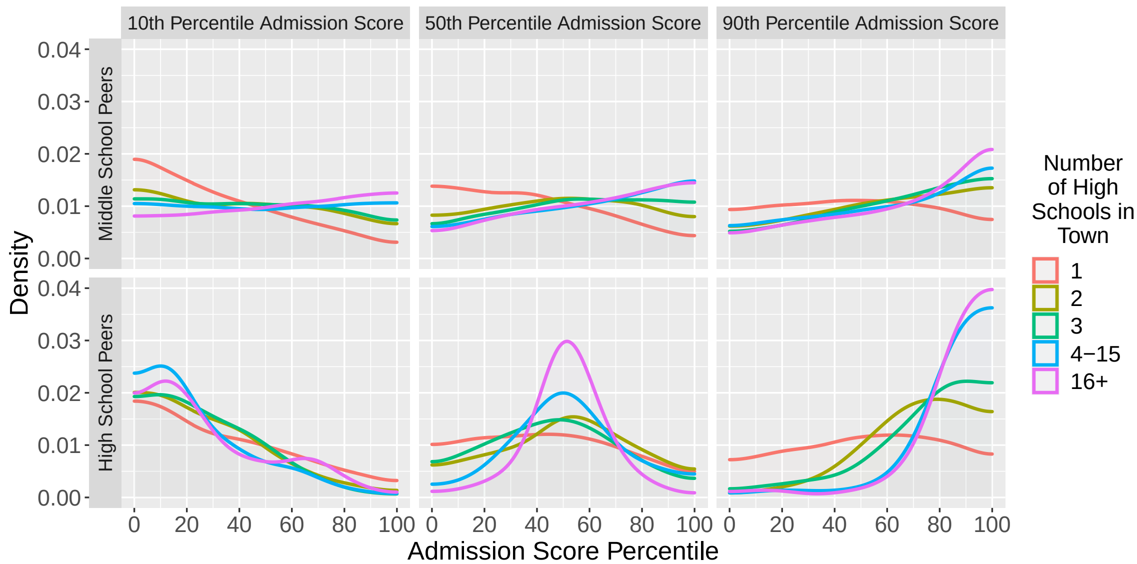

Figure 5: This figure shows peer admission scores vary with own admission score and with the number of high schools in the town, at the end of middle school and the beginning of high school. Each panel shows distributions of peer admission scores for a given own admission score, where peers are defined as students who attend the same middle-school-cohort (top) and high school-track cohort (bottom). The top panels show middle school peer distributions and the bottom panels show high school peer ability distributions.

A.2 Determinants of Number of Schools

Table 9: Determinants of Number of Schools Across Towns

	Dependent variable:		
	Change in Number of Schools (2008-2019)	(2019 Number of Schools)	
	(1)	(2)	(3)
Change in Population (1992-2019, 1,000s)	0.000		0.058
	(0.000)		(0.040)
Population (1992, 1,000s)		0.073^{***}	0.061^{***}
		(0.003)	(0.012)
High School Dropout Rate (County)			−0.919
			(7.328)
Admitted Students (Town-Cohort)			1.368^{***}
			(0.464)
Wages (County, RON)			0.038
			(0.228)
Town Unemployment Rate			0.017^{*}
			(0.010)
Observations	373	5,367	5,291
R^2	0.010	0.969	0.973
Admitted Students (Town-Cohort)^2	No	No	Yes
Population (1992, 1,000s)^2	No	No	Yes
Change in Population (1992-2019, 1,000s)^2	No	No	Yes
County FE	Yes	Yes	No

This table shows the relationship between different town characteristics and the number of high schools. Column 1 shows estimates from a regression of the change in number of high schools across towns and the change in population, between 2008 and 2019. Column 2 shows the correlation between the number of schools in towns in 2019 and the town population in 1992. Column 3 shows estimates of a regression of the number of high schools in towns in 2019 and controls including 1992 population, change in population between 1992 and 2019, admitted students, unemployment rates and county-level wages and high school drop out rates. The strongest determinant of the number of schools remains the 1992 town population.

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.

A.3 Instrumental Variable Additional Results

Table 10: IV First Stage

	Average Peer Exam Score Percentile	
	(School)	(Track)
Admission Score (Percentile)	0.262***	0.325***
d2×n2	−0.002	0.004
d3×n2	0.010	0.009*
d4×n2	0.031***	0.016***
d5×n2	0.055***	0.020***
d6×n2	0.089***	0.031***
d7×n2	0.112***	0.036***
d8×n2	0.126***	0.041***
d9×n2	0.135***	0.050***
d10×n2	0.144***	0.060***
d2×n3	0.008	0.003
d3×n3	0.015*	0.008
d4×n3	0.034***	0.014
d5×n3	0.064***	0.017*
d6×n3	0.112***	0.033***
d7×n3	0.153***	0.048***
d8×n3	0.186***	0.060***
d9×n3	0.206***	0.071***
d10×n3	0.224***	0.084***
d2×n4-15	0.011***	0.005
d3×n4-15	0.039***	0.021***
d4×n4-15	0.073***	0.034***
d5×n4-15	0.123***	0.052***
d6×n4-15	0.185***	0.074***
d7×n4-15	0.248***	0.098***
d8×n4-15	0.298***	0.118***
d9×n4-15	0.337***	0.140***
d10×n4-15	0.366***	0.162***
d2×n16+	0.012**	0.009*
d3×n16+	0.047***	0.034***
d4×n16+	0.091***	0.055***
d5×n16+	0.145***	0.072***
d6×n16+	0.213***	0.095***
d7×n16+	0.279***	0.122***
d8×n16+	0.339***	0.151***
d9×n16+	0.394***	0.186***
d10×n16+	0.440***	0.215***
Number of High Schools in Town	5 bins	5 bins
Town-Cohort Admission Score Decile (d)	Yes	Yes
Number of Students (Town-Cohort)	Yes	Yes
Number of Students (Town-Cohort) × d	Yes	Yes
Town Unemployment Level	Yes	Yes
Town Unemployment Level × d	Yes	Yes
County HS Dropout Rate	Yes	Yes
County HS Dropout Rate × d	Yes	Yes
County Average Wage	Yes	Yes
County Average Wage × d	Yes	Yes
Town FE	533	533
Year FE	12	12
Track FE	116	116
MS FE	18,590	18,590
Observations	1,161,358	1,161,135
Adjusted R^2	0.82	0.86
F-stat	3,538.6	1,000.6
Weak Instrument Test p-value	0	0
Wu-Hausman p-value	0	0

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.

This table shows first stage results form the equation 2. Peer admission scores (at the school level) are instrumented using an interaction between student's own admission score decile and the number of high schools int he town in which they attend high school. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects.

A.4 Other Outcomes

Table 11: IV First Stage (School): Other Outcomes

	Dependent variable:			
	Matched	School Change	Pass Exit Exam	Exit Exam Absence
Admission Score (Percentile)	0.555***	0.230***	0.230***	0.230***
d2 × n2	0.010***	0.001	0.001	0.001
d3 × n2	0.027***	0.010**	0.010**	0.010**
d4 × n2	0.051***	0.028***	0.028***	0.028***
d5 × n2	0.087***	0.049***	0.049***	0.049***
d6 × n2	0.129***	0.080***	0.080***	0.080***
d7 × n2	0.163***	0.103***	0.103***	0.103***
d8 × n2	0.182***	0.116***	0.116***	0.116***
d9 × n2	0.192***	0.126***	0.126***	0.126***
d10 × n2	0.195***	0.135***	0.135***	0.135***
d2 × n3	0.007	0.006	0.006	0.006
d3 × n3	0.026***	0.015**	0.015**	0.015**
d4 × n3	0.054***	0.033***	0.033***	0.033***
d5 × n3	0.091***	0.062***	0.062***	0.062***
d6 × n3	0.149***	0.108***	0.108***	0.108***
d7 × n3	0.205***	0.147***	0.147***	0.147***
d8 × n3	0.249***	0.178***	0.178***	0.178***
d9 × n3	0.274***	0.198***	0.198***	0.198***
d10 × n3	0.297***	0.216***	0.216***	0.216***
d2 × n4-15	0.009***	0.008**	0.008**	0.008**
d3 × n4-15	0.026***	0.031***	0.031***	0.031***
d4 × n4-15	0.058***	0.064***	0.064***	0.064***
d5 × n4-15	0.114***	0.112***	0.112***	0.112***
d6 × n4-15	0.179***	0.170***	0.170***	0.170***
d7 × n4-15	0.256***	0.228***	0.228***	0.228***
d8 × n4-15	0.324***	0.275***	0.275***	0.275***
d9 × n4-15	0.374***	0.313***	0.313***	0.313***
d10 × n4-15	0.414***	0.342***	0.342***	0.342***
d2 × n16+	−0.004	0.006	0.006	0.006
d3 × n16+	0.017**	0.033***	0.033***	0.033***
d4 × n16+	0.061***	0.075***	0.075***	0.075***
d5 × n16+	0.125***	0.127***	0.127***	0.127***
d6 × n16+	0.208***	0.190***	0.190***	0.190***
d7 × n16+	0.289***	0.252***	0.252***	0.252***
d8 × n16+	0.364***	0.308***	0.308***	0.308***
d9 × n16+	0.435***	0.360***	0.360***	0.360***
d10 × n16+	0.510***	0.405***	0.405***	0.405***
Observations	2,166,575	1,341,775	1,341,775	1,341,775
R^2	0.74	0.80	0.80	0.80

This table shows second stage results from the first stage of a 2SLS least square regression of several outcomes: 1) admission-graduation match rate (a proxy of dropout rate), 2) change of school rate, 3) exit exam pass rate and 4) exit exam absenteeism rate on peer admission score (instrumented by student's own admission rank and number of high schools in their town). The top panel shows results from separate regressions using high school peers and the bottom panel shows results from regressions using track-level peers. Controls include within town-cohort own admission score decile and interactions of these decile dummies with: the number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data). Additional controls include the number of high schools in town (grouped into 4 bins), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.

Table 12: IV First Stage (Track): Other Outcomes

	Dependent variable:			
	Matched	School Change	Pass Exit Exam	Exit Exam Absence
Admission Score (Percentile)	0.606***	0.302***	0.302***	0.302***
d2 × n2	0.017***	0.006*	0.006*	0.006*
d3 × n2	0.040***	0.011**	0.011**	0.011**
d4 × n2	0.070***	0.015***	0.015***	0.015***
d5 × n2	0.109***	0.018***	0.018***	0.018***
d6 × n2	0.151***	0.027***	0.027***	0.027***
d7 × n2	0.186***	0.032***	0.032***	0.032***
d8 × n2	0.213***	0.037***	0.037***	0.037***
d9 × n2	0.235***	0.047***	0.047***	0.047***
d10 × n2	0.248***	0.058***	0.058***	0.058***
d2 × n3	0.013***	0.003	0.003	0.003
d3 × n3	0.041***	0.010	0.010	0.010
d4 × n3	0.076***	0.014	0.014	0.014
d5 × n3	0.115***	0.017*	0.017*	0.017*
d6 × n3	0.169***	0.032***	0.032***	0.032***
d7 × n3	0.217***	0.045***	0.045***	0.045***
d8 × n3	0.257***	0.057***	0.057***	0.057***
d9 × n3	0.283***	0.068***	0.068***	0.068***
d10 × n3	0.307***	0.084***	0.084***	0.084***
d2 × n4-15	0.015***	0.006	0.006	0.006
d3 × n4-15	0.038***	0.018***	0.018***	0.018***
d4 × n4-15	0.072***	0.028***	0.028***	0.028***
d5 × n4-15	0.123***	0.044***	0.044***	0.044***
d6 × n4-15	0.176***	0.064***	0.064***	0.064***
d7 × n4-15	0.235***	0.086***	0.086***	0.086***
d8 × n4-15	0.286***	0.105***	0.105***	0.105***
d9 × n4-15	0.326***	0.126***	0.126***	0.126***
d10 × n4-15	0.364***	0.150***	0.150***	0.150***
d2 × n16+	0.007*	0.005	0.005	0.005
d3 × n16+	0.034***	0.024***	0.024***	0.024***
d4 × n16+	0.077***	0.042***	0.042***	0.042***
d5 × n16+	0.133***	0.057***	0.057***	0.057***
d6 × n16+	0.198***	0.078***	0.078***	0.078***
d7 × n16+	0.258***	0.103***	0.103***	0.103***
d8 × n16+	0.313***	0.129***	0.129***	0.129***
d9 × n16+	0.367***	0.161***	0.161***	0.161***
d10 × n16+	0.428***	0.193***	0.193***	0.193***
Observations	2,165,841	1,341,062	1,341,062	1,341,062
R^2	0.77	0.84	0.84	0.84

This table shows second stage results from the first stage of a 2SLS least square regression of several outcomes: 1) admission-graduation match rate (a proxy of dropout rate), 2) change of school rate, 3) exit exam pass rate and 4) exit exam absenteeism rate on peer admission score (instrumented by student's own admission rank and number of high schools in their town). The top panel shows results from separate regressions using high school peers and the bottom panel shows results from regressions using track-level peers. Controls include within town-cohort own admission score decile and interactions of these decile dummies with: the number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data). Additional controls include the number of high schools in town (grouped into 4 bins), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.

A.5 School Openings

Table 13: List of HS Openings

Number of HS (before opening)	Occurences	First Full Cohort Graduation Year
1	2	2017 (2)
2	2	2011 (2)

Note: This table contains information on the high school openings retained for the analysis. The "First Full Cohort Graduation Year" indicates the graduation year of the first students that completed all four years in the newly opened high school.

A.6 School Spending

Table 14: School Expenditure vs Entrance Grades

	Dependent variable:			
	Average School Expenditure per Student per Year (€)			
	Across Towns		Within Towns	
	(1)	(2)	(3)	(4)
d2	−5.243***	−3.634***	−5.260***	−3.876***
d3	−9.829***	−6.606***	−8.089***	−5.553***
d4	−13.590***	−8.498***	−10.105***	−6.930**
d5	−14.877***	−9.170***	−12.657***	−9.214***
d6	−16.045***	−10.320***	−14.596***	−11.885***
d7	−19.013***	−14.197***	−14.847***	−12.939***
d8	−19.692***	−15.765***	−16.042***	−14.326***
d9	−21.636***	−17.488***	−17.032***	−15.279***
d10	−24.773***	−19.487***	−18.227***	−16.135***
High School Cohort Size		−10.114***		−8.550***
Town FE (1+359)	No	No	Yes	Yes
Year FE (1+11)	Yes	Yes	Yes	Yes
Within-Town-Year Deciles	No	No	Yes	Yes
National-Year Deciles	No	No	Yes	Yes
Observations	390,085	390,085	390,085	390,085
Adjusted R^2	0.205	0.232	0.419	0.428

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level. This table shows the relationship between per student school expenditures and student entrance scores. Reference level is students with first decile entrance scores. Deciles (d) are student entrance exam deciles (national, for columns 1 and 2, within cohort-town for column 3 and 4); reference level is the bottom entrance grade decile (d1). High school cohort sizes are standardized.

Table 15: Graduation Grades vs School Spending

	Dependent variable:			
	Graduation Grade Percentile			
	(1)	(2)	(3)	(4)
Entrance Grade Percentile	0.701***	0.676***	0.663***	0.670***
School Spending	−0.019***	0.002	0.013	0.013
Small Towns		0.059***	0.024	0.055*
Medium Towns		0.072***	−0.034	0.036
Large Towns		0.086***	−0.072	0.061
School Spending × Small Towns		−0.016***	−0.021	−0.019
School Spending × Medium Towns		−0.028***	−0.035**	−0.033**
School Spending × Large Towns		−0.029**	−0.043**	−0.036*
Town FE (1+359)	No	No	Yes	Yes
Year FE (1+11)	No	No	No	Yes
Observations	273,048	273,048	273,048	273,048
Adjusted R^2	0.436	0.443	0.474	0.487

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the town level.
This table shows the relationship between school spending per student and graduation grades. Small Towns have 2-6 HS, Medium Towns have 7-15 HS, Large towns have 16+ HS; reference level is towns with one HS. School Spending is the average yearly school spending per graduating student, in €100.

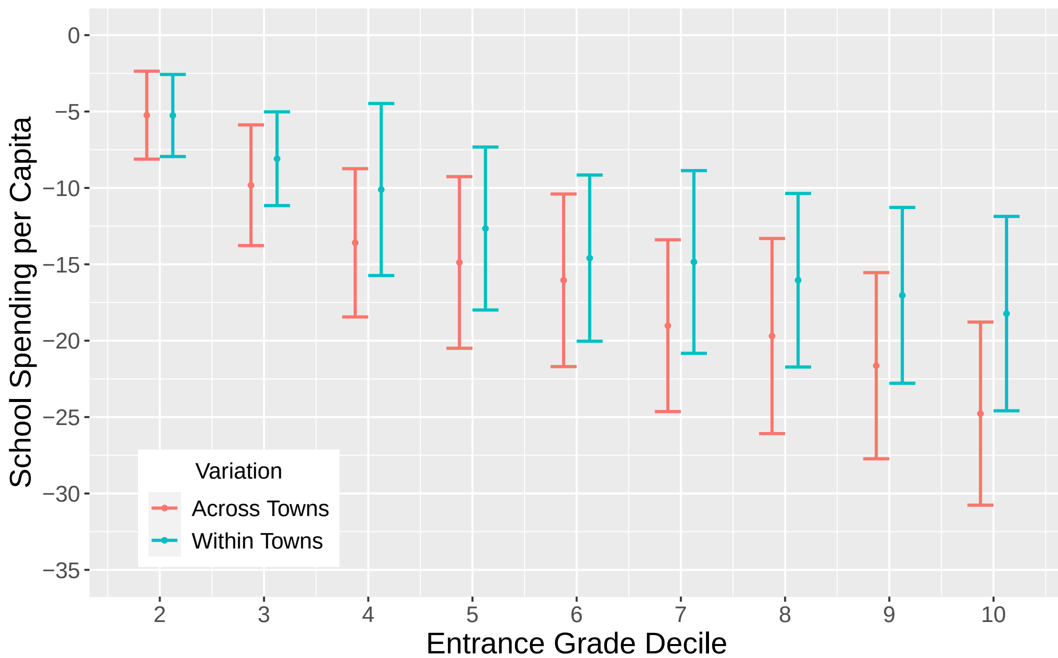

Figure 6: This figure shows the relationship between per student school expenditures and student entrance scores. Reference level is students with first decile entrance scores

B Notes on Matching

In this section, I will briefly discuss the matching of graduation records to admission records. Matching is conducted by student name (as no unique student identifier exists) within high schools. Thus, students who drop out or change high schools will not be matched. As a note, high school changes can occur for legitimate reasons (moving, for example) and, anecdotally, due to corruption.

Table 16 shows summary statistics regarding yearly match rates. Several additional factors, aside from drop outs and transfers, negatively impact the match rate. Students in many programs write the high school graduation exam, but do not enter high school via the national admission exam. For example, students in religious, arts, teaching, sports and architecture, may be admitted based on other aptitudes, such as playing an instrument, sporting prowess, knowledge of the Bible, drawing skills, etc. Students in these tracks will not appear in the admission records. Moreover, some students may repeat a year, while others are former drop-outs who decide to complete their high school studies.

Likewise, not all high school students admitted to high schools complete the high school program write the graduation exam. This is the case with students in low-ranked schools and typically in non-academic or technical programs that aim to prepare students for tertiary education. Furthermore, students who do not feel confident of passing the exit exam will sometimes not register for it.

Regarding year to year variation in match rates, generally speaking, the match rate improves with time. This may be a sign of better data quality or of enforcement of school switching, as well as changes in drop-out rates.

Table 16: Statistics Regarding Yearly Match Rates of Graduating and Entering Students

	Min	Q1	Median	Mean	Q3	Max
Graduating Students	56%	59%	64%	66%	71%	75%
Entering Students	48%	52%	59%	59%	66%	67%
Graduating Students (filtered)	58%	64%	79%	74%	84%	85%
Graduating Students (filtered and excluding technical tracks)	67%	73%	84%	80%	85%	86%

Note: This table contains summary statistics regarding yearly match rates between entering and graduating students. The third line shows match rates for graduating students, after filtering arts, music, education, architecture, sports and religious track students, who typically are not admitted through the regular admission exam, as well as graduating students from previous cohorts. The fourth line also excludes all technical track students, some of which (depending on their track), do not gain admission through the entrance exam.

C Identification Concerns and Robustness Checks

C.1 Migration

Table 17: IV Second Stage (School): Endogenous Markets

	Dependent variable:		
	Graduation Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.592***	0.566***	0.516***
Instrumented Peer Admission Score (Percentile)	0.183***	0.134***	0.185***
Number of High Schools in Town	4	4	4
Town-Cohort Admission Score Decile (d)	No	Yes	Yes
Number of Students (Town-Cohort)	No	No	Yes
Number of Students (Town-Cohort) × d	No	No	Yes
Town Unemployment Level	No	No	Yes
Town Unemployment Level × d	No	No	Yes
County HS Dropout Rate	No	No	Yes
County HS Dropout Rate × d	No	No	Yes
County Average Wage	No	No	Yes
County Average Wage × d	No	No	Yes
Market FE	No	351	346
Year FE	No	12	12
Track FE	No	191	191
MS FE	No	18,592	18,590
Observations	1,180,088	1,180,088	1,161,360
Adjusted R^2	0.524	0.638	0.639

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows second stage results form the equation 2. Student graduation exams scores (in percentiles at the cohort-country level) are regressed on similar admission scores and peer admission scores. Peer admission scores (at the school level) are instrumented using an interaction between student's own admission score decile and the number of high schools in the education markets in which they attend high school. Education markets are defined endogenously based on student flows between middle schools and high schools across locations. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects.

Table 18: IV Second Stage (School): Endogenous Markets, Excluding Migrants

	Dependent variable:		
	Graduation Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.584***	0.555***	0.510***
Instrumented Peer Admission Score (Percentile)	0.169***	0.118***	0.165***
Number of High Schools in Town	4	4	4
Town-Cohort Admission Score Decile (d)	No	Yes	Yes
Number of Students (Town-Cohort)	No	No	Yes
Number of Students (Town-Cohort) × d	No	No	Yes
Town Unemployment Level	No	No	Yes
Town Unemployment Level × d	No	No	Yes
County HS Dropout Rate	No	No	Yes
County HS Dropout Rate × d	No	No	Yes
County Average Wage	No	No	Yes
County Average Wage × d	No	No	Yes
Market FE	No	350	345
Year FE	No	12	12
Track FE	No	191	191
MS FE	No	18,850	18,436
Observations	1,071,919	1,071,919	1,054,428
Adjusted R^2	0.524	0.638	0.639

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows second stage results form the equation 2. Student graduation exams scores (in percentiles at the cohort-country level) are regressed on similar admission scores and peer admission scores. Peer admission scores (at the school level) are instrumented using an interaction between student's own admission score decile and the number of high schools in the education markets in which they attend high school. Education markets are defined endogenously based on student flows between middle schools and high schools across locations. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Results exclude students migrating between markets.

Table 19: IV Second Stage (Track): Endogenous Markets

	Dependent variable:		
	Graduation Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.491***	0.521***	0.427***
Instrumented Peer Admission Score (Percentile)	0.334***	0.246***	0.395***
Number of High Schools in Town	4	4	4
Town-Cohort Admission Score Decile (d)	No	Yes	Yes
Number of Students (Town-Cohort)	No	No	Yes
Number of Students (Town-Cohort) × d	No	No	Yes
Town Unemployment Level	No	No	Yes
Town Unemployment Level × d	No	No	Yes
County HS Dropout Rate	No	No	Yes
County HS Dropout Rate × d	No	No	Yes
County Average Wage	No	No	Yes
County Average Wage × d	No	No	Yes
Market FE	No	351	346
Year FE	No	12	12
Track FE	No	191	191
MS FE	No	18,592	18,590
Observations	1,179,769	1,179,769	1,161,051
Adjusted R^2	0.522	0.639	0.637

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows second stage results form the equation 2. Student graduation exams scores (in percentiles at the cohort-country level) are regressed on similar admission scores and peer admission scores. Peer admission scores (at the track level) are instrumented using an interaction between student's own admission score decile and the number of high schools in the education markets in which they attend high school. Education markets are defined endogenously based on student flows between middle schools and high schools across locations. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects.

Table 20: IV Second Stage (Track): Endogenous Markets, Excluding Migrants

	Dependent variable:		
	Graduation Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.493***	0.517***	0.432***
Instrumented Peer Admission Score (Percentile)	0.308***	0.214***	0.354***
Number of High Schools in Town	4	4	4
Town-Cohort Admission Score Decile (d)	No	Yes	Yes
Number of Students (Town-Cohort)	No	No	Yes
Number of Students (Town-Cohort) × d	No	No	Yes
Town Unemployment Level	No	No	Yes
Town Unemployment Level × d	No	No	Yes
County HS Dropout Rate	No	No	Yes
County HS Dropout Rate × d	No	No	Yes
County Average Wage	No	No	Yes
County Average Wage × d	No	No	Yes
Market FE	No	350	345
Year FE	No	12	12
Track FE	No	191	191
MS FE	No	18,849	18,435
Observations	1,071,670	1,071,670	1,054,185
Adjusted R^2	0.522	0.639	0.638

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows second stage results form the equation 2. Student graduation exams scores (in percentiles at the cohort-country level) are regressed on similar admission scores and peer admission scores. Peer admission scores (at the track level) are instrumented using an interaction between student's own admission score decile and the number of high schools int he town in which they attend high school. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Results exclude students migrating between markets.

C.2 Heckman Selection

The Heckman selection procedure implemented uses the proportion of a student's middle school classmates who drop out of high school, interacted with a student's grade in a probit model to predict a student's probability of dropping out, as per Wooldridge (2002). The idea is that a student's middle school peers may exert indirect influence on a student's decision to drop out, without having an influence on student performance at school, conditional on the student's entrance score and middle school attended. Then, the estimates of this model are used to compute an inverse Mills ratio (λ) used as a regressor in the first and second stages of the IV estimation. First, the sample selection equation, which includes all exogenous variables, is estimated via probit:

$$\begin{aligned}\text{drop}_i =&\mathbb{1}[\psi_0 + \psi_m \text{ms drop}_{my} + \psi_{md}\text{ms drop}_{my} \times \delta_d + \psi_e e_i + \delta_n + \delta_d + \delta_l + \delta_m + \\ &\delta_p + \delta_y + \delta_s + \delta_{s\times d} + \epsilon_i]\end{aligned}$$

where drop_i is a an indicator of whether student i dropped out from high school (i.e. they have a high school entrance grade, but no corresponding graduation grade), ms drop_{my} is the proportion of high school drop outs in cohort y of middle school m. The inverse Mills ratio is computed as:

$$\lambda_i = \frac{\phi(\widehat{\text{drop}_i})}{\Phi(\widehat{\text{drop}_i})}$$

where ϕ is the standard normal probability density function and Φ is the standard normal cumulative probability function. The first and second stages of the IV estimation will then include this new variable. The second stage is:

$$g_i = \beta_0 + \beta_e e_i + \beta_\mu \mu^e_{\text{-ihy}} + \delta_n + \delta_d + \delta_l + \delta_m + \delta_p + \delta_y + \delta_s + \delta_{s\times d} + \beta_\lambda \lambda_i + \epsilon_i$$

and the first stage is:

$$\mu^e_{hy} = \gamma_0 + \gamma_e e_i + \eta_n + \eta_d + \boldsymbol{\eta_{d\times n}} + \eta_m + \eta_l + \eta_p + \eta_y + \eta_s + \eta_{s\times d} + \eta_\lambda \lambda_i + \xi_i$$

The results of the selection equation are presented in Table 21. Conditional on their entrance scores and ranking within town-cohort, students who attended a high drop-out rate middle school are more likely to drop out of high school, and this effect is more pronounced for students with relatively low entrance grades. For students in the lowest decile of the entrance grade distribution in their town, attending a middle school with a one percentile point higher drop-out rate is associated to a 0.9 to 1 percent higher chance of dropping out during high school, on average. For top entrance score students, increases in the high school drop out rates of their middle school peers are associated to a 0.6-0.7 percent higher increases in drop-out rates.

The second stage results at the school (track) are presented in Table 23 (22). The main takeaway is that the coefficient of interest, estimating the effect of attending a school with higher entrance scores, do not qualitatively differ from the results that do not take sample selection into account.

Table 21: Probit for High School Dropping Out Probability: Marginal Effects

	Dependent variable:		
	Probability of Dropping out During High School		
	(1)	(2)	(3)
Admission Score (Percentile)	-0.654^{***}	-0.600^{***}	-0.608^{***}
Middle School Drop Out Rate	0.573^{***}	0.585^{***}	0.585^{***}
Number of High Schools in Town	4	4	4
Town-Cohort Admission Score Decile (d)	No	Yes	Yes
Number of Students (Town-Cohort)	No	No	Yes
Number of Students (Town-Cohort) $\times$ d	No	No	Yes
Town Unemployment Level	No	No	Yes
Town Unemployment Level $\times$ d	No	No	Yes
County HS Dropout Rate	No	No	Yes
County HS Dropout Rate $\times$ d	No	No	Yes
County Average Wage	No	No	Yes
County Average Wage $\times$ d	No	No	Yes
Town FE	No	552	544
Year FE	No	12	12
MS FE	No	18,592	18,590
Observations	1,179,769	1,179,769	1,161,051

Note: *p<0.1; **p<0.05; ***p<0.01.
This table shows marginal effects from a probit regression of an individual high school dropout indicator on covariates including student high school admission scores and the average high school drop out rate in students' middle school of origin. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects and middle school fixed effects.

Table 22: IV Second Stage (Track Level) with Heckman Correction

	Dependent variable:		
	Graduation Exam Score (Percentile)		
	(1)	(2)	(3)
Admission Score (Percentile)	0.367***	0.322***	0.356***
Inverse Mills Ratio	0.086***	0.005	0.005
Instrumented Peer Admission Score (Percentile)	0.341***	0.246***	0.353***
Number of High Schools in Town	4	4	4
Town-Cohort Admission Score Decile (d)	No	Yes	Yes
Number of Students (Town-Cohort)	No	No	Yes
Number of Students (Town-Cohort) × d	No	No	Yes
Town Unemployment Level	No	No	Yes
Town Unemployment Level × d	No	No	Yes
County HS Dropout Rate	No	No	Yes
County HS Dropout Rate × d	No	No	Yes
County Average Wage	No	No	Yes
County Average Wage × d	No	No	Yes
Town FE	No	552	544
Year FE	No	12	12
MS FE	No	18,592	18,590
Observations	1,179,769	1,179,769	1,161,051

Note: *p<0.1; **p<0.05; ***p<0.01.

This table shows second stage results form the equation 2. Student graduation exams scores (in percentiles at the cohort-country level) are regressed on similar admission scores and peer admission scores. Peer admission scores (at the school level) are instrumented using an interaction between student's own admission score decile and the number of high schools int he town in which they attend high school. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects and middle school fixed effects.

Table 23: IV Second Stage (School Level) with Heckman Correction

	Dependent variable:		
	Graduation Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.337***	0.522***	0.517***
Inverse Mills Ratio	0.091***	0.006	0.005
Instrumented Peer Admission Score (Percentile)	0.206***	0.163***	0.175***
Number of High Schools in Town	4	4	4
Town-Cohort Admission Score Decile (d)	No	Yes	Yes
Number of Students (Town-Cohort)	No	No	Yes
Number of Students (Town-Cohort) × d	No	No	Yes
Town Unemployment Level	No	No	Yes
Town Unemployment Level × d	No	No	Yes
County HS Dropout Rate	No	No	Yes
County HS Dropout Rate × d	No	No	Yes
County Average Wage	No	No	Yes
County Average Wage × d	No	No	Yes
Town FE	No	552	544
Year FE	No	12	12
MS FE	No	18,592	18,590
Observations	1,180,088	1,180,088	1,161,360
Adjusted R^2	0.537	0.644	0.645

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows second stage results form the equation 2. Student graduation exams scores (in percentiles at the cohort-country level) are regressed on similar admission scores and peer admission scores. Peer admission scores (at the school level) are instrumented using an interaction between student's own admission score decile and the number of high schools int he town in which they attend high school. Controls include the number of high schools in town (grouped into 4 bins), within town-cohort own admission score decile, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects.

C.3 Robustness Check: Overidentification

Table 24: IV Second Stage: Only Two Instruments

	Dependent variable:	
	Graduation Exam Score Percentile	
	School	Track
Instrumented Peer Admissiom Score (Percentile)	0.179***	0.398***
	(0.026)	(0.058)
Admission Score (Percentile)	0.528***	0.436***
	(0.027)	(0.037)
Number of High Schools in Town	4	4
Town-Cohort Admission Score Decile (d)	Yes	Yes
Number of Students (Town-Cohort)	Yes	Yes
Number of Students (Town-Cohort) × d	Yes	Yes
Town Unemployment Level	Yes	Yes
Town Unemployment Level × d	Yes	Yes
County HS Dropout Rate	Yes	Yes
County HS Dropout Rate × d	Yes	Yes
County Average Wage	Yes	Yes
County Average Wage × d	Yes	Yes
Town FE	552	544
Year FE	12	12
Track FE	191	190
MS FE	18,592	18,590
Observations	1,161,360	1,161,051
Adjusted R^2	0.645	0.643
Weak Instrument Test p-value	0	0
Sargan p-value (1st stage)	0.99988	0.999791
Wu-Hausman p-value	0	0

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level. This table shows second stage results form the equation 2. Student graduation exams scores (in percentiles at the cohort-country level) are regressed on similar admission scores and peer admission scores. Peer admission scores (at the school level) are instrumented using an interaction between student's own admission score decile and the number of high schools in the education markets in which they attend high school. Education markets are defined endogenously based on student flows between middle schools and high schools across locations. Controls include the number of high schools in town (grouped into 2 bins), whether student admission score is above median in their town-cohort, number of students admitted in towns in a given year, town unemployment level and county high school dropout levels and average wage levels (all computed as averages of 2010-2019 yearly data), town fixed effects, year fixed effects, track type fixed effects and middle school fixed effects. Results exclude students migrating between markets.

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