School Choice, Student Sorting and Academic Performance[†]

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September 20, 2021

Abstract

In this paper, I first study the effects of school choice on student sorting patterns and academic performance. Second, I explore possible channels through which sorting impacts performance. The main finding is that school choice greatly increases the dispersion in test scores rather than acting as a "tide that lifts all boats". The setup I study is Romanian high schools, where students compete for seats based on national standardized exams. I scrape and construct a novel dataset matching twelve years and more than two million student admission and graduation records, teacher hiring records and school spending records. I first show that having more schools to choose from increases student sorting. I find that across towns of similar sizes, whenever there are more schools to choose from, student sorting by ability across schools is more pronounced. Second, using this variation in school numbers across similar locations, I show that increases in student sorting causally benefit high-scoring students and hinder low-scoring students, thus increasing outcome inequalities. I confirm these findings by focusing on high school openings in small towns. Openings lead to increases in student sorting across schools and result in higher score gaps between high- and low-ability students. Lastly, I use teacher and expenditure data to show that observed effects on student scores can mainly be attributed differences in teachers across schools (48%), compared to peer effects (25%) and school spending (5%). My result suggest that increased school choice leads to a polarization in student outcomes that is driven by high-scoring students sorting into schools with better teachers and better peers.

JEL Classification : I21, I24, H52
Keywords: education, sorting, inequality, peers, teachers

[†]A previous version of this paper circulated under the title "Student Sorting and Academic Performance".

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I am deeply indebted to Fabian Lange, Francesco Amodio and Nicolas Gendron-Carrier for excellent supervision and advice, as well as Christopher Barrington-Leigh, Rui Castro, Ana-Maria Dimand, Rohan Dutta, John Galbraith, Andra Hiriscau, John Klopfer, Laura Lasio, Daniela Morar, Markus Poschke, Fernando Saltiel, Xian Zhang and all the seminar participants and organizers at McGill University, Goethe University, UQAM, University of Pittsburgh, GEEZ, Nederlandse Economenweek 2020 and the E-conomics of Education Graduate Student Workshop. I am also indebted to Andreea Mitrut, Gabriel Kreindler, Cristian Pop-Eleches and Diana Coman for help on obtaining the data used for this study. All errors are my own.

1 Introduction

In this paper, I attempt to shed light on the claim that school choice can act as a "rising tide that lifts all boats" (e.g. Hoxby (2007)). The implication is that expanding school choice would exert competitive pressures on schools, forcing them to improve their service or risk losing students. In the United States in particular, where student literacy and numeracy levels have stagnated for the past decades, school choice has often been presented as a panacea. However, the system-wide implications of school choice have been difficult to prove, especially since a very small proportion of students attend schools operating under school choice and these schools tend to be high-quality, selective schools.

In this paper, I first study the link between school choice, student sorting patterns and subsequent student performance, in the context of Romanian high schools. Unlike in the US, Romanian high school admissions are fully based on school choice. Students compete for seats in schools across the country based on standardized exam scores. This allows me to study the system-wide implications of school choice. To this end, I put together a dataset covering the universe of Romanian high school students across 11 years (2004-2015 entering cohorts). These data consist of more than two million students originating from more than 10,000 middle schools and attending close to 1,500 high schools across more than 500 towns. I augment these data by adding detailed geographic information on the location of the middle and high schools.

Second, I explore the underlying channels through which school choice ultimately affects student performance. I match the student admission and graduation records to novel, web scraped data on the universe of teacher hires over five years. These data include teacher exam scores on subject-specific exams used to allocate them to teaching jobs and education, experience and GPA information and cover close to 200,000 teacher exam scores and in excess of 40,000 teacher hires. I build a dataset containing all high school expenditures on goods and services for more than ten years, totaling more than a million transactions. I thus have unique data, rich in information on students, locations, inputs, and teachers that I leverage to study sorting on ability, its effects on academic performance, and the mechanisms through which sorting affects academic performance.

The causal effect of student sorting on academic performance is difficult to identify because school choices are endogenous. I overcome this issue in two ways. First, I exploit mechanically-arising variation in sorting patterns induced by differences in high school numbers across towns of similar sizes. In Romania, a national entrance exam determines high school admissions. High-scoring students have priority over low-scoring ones when it comes to high school choices. Students can then sort across high schools along entrance grades at will. As a result, student sorting levels are high across the country. Moreover, this setup induces differences in sorting patterns across towns with similar populations but different numbers of high schools. For example, a high entrance grade student in a town with two high schools can sort into a much more selective high school than their counterpart in a similar-sized town with only one high school. By interacting student entrance scores with number of high schools in their towns, I construct an instrument that shifts the type of high school students attend. This allows me to compare graduation scores of similar-ability students across otherwise comparable towns that differ only in the number of high schools to identify the effects of sorting.

Second, I use new high school openings in towns with few high schools in a triple difference framework. The data's panel nature allows me to key in specifically on school openings, which disrupt preexisting sorting patterns. A new school opening disrupts sorting patterns at the local level. More specifically, I measure how a school opening differentially affects high-ability and low-ability students by comparing them to their counterparts in similarly-sized towns where there are no new schools opening.

Lastly, I disentangle the channels through which 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. Leveraging differences in peer entrance scores across cohorts within the same high schools and differences in teacher examination grades and per-student school expenditures across high schools, I measure these three channels' relative contribution toward student performance.

I contribute directly to the literature on student tracking and sorting, which has mixed findings. While some studies find that tracking or school choice increase dispersion of outcomes between high- and low-ability students,[1] others find that tracking can benefit both low-ability students and high-ability ones.[2] One reason behind these mixed finding is the fact that student sorting and its effects on learning are very context-specific. For example, in terms of peers and access to high-ability teachers and other learning resources, student sorting in rural sub-Saharan Africa, where students of very different ages and abilities are often pooled into one classroom, has very different implications than in large urban areas in the Unites States, where sorting often leads to unequal access to teaching resources. Thus, studying the channels through which sorting impact performance and their relative importance is crucial if we are to gain any understanding about the ways in which sorting affects student outcomes.

My main results follow. Student sorting along ability is more prevalent in towns with more high schools, even after controlling for student population. The largest jump in sorting occurs between towns with one high school, in which no sorting at the school level is possible, and comparable towns with two high schools. This suggests that the number of schools is the main driver of student sorting.

The instrumental variable approach suggests that conditional on student entrance score, attending a high school with a 1 percentile higher average entrance score increases a student's graduation score by 0.16 percentiles. This has two implications on graduation scores. First, increasing sorting levels are accountable for widening graduation score gaps between high- and low-ability students within towns. Thus, this gap is larger in many-high school towns, which experience high degrees of sorting. More specifically, in locations with more than 15 high schools, the high levels of sorting at the school levels lead to a 12 percentile widening of the performance gap between top entrance score decile students and their counterparts in the lowest decile. In towns with only one high school, this figure shrinks to 3 percentiles.

Additionally, sorting widens the performance gap between urban high-ability students (who can attend selective schools) and rural high-ability students (who cannot). The gap between low-ability urban students (who attend the worst urban schools) and low-ability rural students (who benefit from low sorting in rural areas) shrinks via sorting. Sorting at the school levels

[1] Hanushek and Wößmann (2006), Malamud and Pop-Eleches (2011), Imberman (2011), Pop-Eleches and Urquiola (2013), Chmielewski (2014) and Jakubowski et al. (2016)

[2] Figlio and Page (2002), Duflo et al. (2011) and Collins and Gan (2013).

is responsible for a 4 percentile widening of the graduation score gap between top entrance grade decile students in cities and their counterparts who attend school towns with only one high school. At the other end of the distribution, sorting causes low entrance score students in cities to underperform compared to their counterparts in one high school towns by 4 percentiles. These findings are persistent even when controlling for town fixed effects, student populations across locations and interactions between student populations and entrance scores. Thus, the results are not driven by differences in town sizes. There is a strong sense that, conditional on town size and own entrance score, the number of high schools in a location directly impacts student scores via sorting.

The results generated from school openings confirm these findings: the opening of a new school disproportionately benefits high-ability students who can self-select into the best school, while low-ability students become increasingly segregated into worse schools. A school's opening in a small town leads to a 4 to 10 percentile widening of the graduation gap between top entrance score quartile students and their counterparts in the lowest quartile, compared to similar towns without new school openings. Moreover, there is evidence that a school opening lowers average graduation scores in a town, conditional on student entrance grades.

I proceed to a decomposition of the channels through which sorting into a better school impacts grades. Overall, the three channels I study (peer effects, teacher ability and school expenditures) explain roughly 78% of the effect of attending a better high school. Differences in teacher ability and peer effects each explain 48% and 25% of the total effects of attending a better high school, while differences in school spending only explain 5% of the total effect.

I conduct several robustness checks. First, I adjust for students dropping out of high school (or out of my data) using a Heckman correction. I then address the potentially endogenous migration of students between towns by defining local education markets endogenously. I use them as the unit of analysis instead of towns. Lastly, my models allow similar entrance grade students from towns (or markets) with different populations to perform differently on the graduation exam. This captures the fact that similar-ability students in towns of different sizes face potentially different levels of income, socioeconomic inequality, parent education, etc. The results are robust to all these different specifications.

As a secondary set of results, I explore how student sorting correlates with teacher sorting, school expenditures, and student achievement at graduation. This sheds light on the possible channels through which sorting impacts student achievement. The analysis delivers four sets of results.

First, using data from teacher examinations used to assign teachers to teaching jobs, I find that teacher sorting patterns mirror those of students: high-ability teachers sort into schools with high-ability students. Moreover, conditional on ability, students in schools with better teachers score higher on the graduation exam. On average, a one percentile point higher grade on teacher examinations is associated to a 0.08 increase in student graduation score on that subject, conditional on student ability. This estimate is likely a lower bound, as the data do not allow for student-teacher matching at the classroom level, only at the school level and teacher data contain only newly-hired teachers, excluding teachers who were already employed. Lastly, there are complementarities between student and teacher abilities: high-ability students benefit from high-ability teachers more than low-ability students.

Second, using year to year quasi-random variation in the abilities of entering cohorts within a school to identify potential peer effects. While, on average, peer effects are not significant, there is evidence that this effect is heterogeneous in students' ranking within their track. Higher ability students within their tracks or schools benefit more from increases in peer admission scores. A one percentile increase in average peer entrance score at the school level increases top student graduation grades by 0.17 percentiles on average. Lowest entrance score students' graduation grades are negatively impacted, with a magnitude of 0.10.[3]

Third, there is no evidence that school spending on goods and services improves student scores. Although low-admission score students in Romania attends schools with higher levels of per-student spending, both nationally and within towns, this does not translate into higher scores at graduation, conditional on admission scores and teacher ability.

Several policy implications follow from this analysis. First of all, policies that increase

[3]This is consistent with so-called "single crossing" peer effects models. See Sacerdote (2011) for more details. This is also consistent with survey evidence by Pop-Eleches and Urquiola (2013), who document higher instances of bullying aimed at low-ability students within Romanian high schools, leading to marginalization.

student segregation on ability (for example, school choice policies or tracking) exacerbate performance gaps between high- and low-achieving students and between top urban and top rural students. In particular, low-ability students in urban areas emerge as the most negatively affected group by sorting and school choice. On the bright side, my results suggest that the exacerbation of inequalities caused by student sorting can be mitigated by incentivizing high-ability teachers to work in low-ranking schools. However, this may be socially wasteful, as there is evidence that high-ability students disproportionately benefit from being taught by high-ability teachers. Thus, reallocating top teachers to bad schools may not be a particularly efficient allocation of teaching resources.

Second, school openings, especially when there is significant school choice, may not benefit students equally. The findings suggest that school openings, in particular in small towns, disproportionately benefit high-ability students. These students benefit from the increase in school-level sorting following the opening of a new school. After the opening, they are separated from their low-ability counterparts, who are segregated into low-quality schools. Thus, policymakers have to be very mindful of sorting effects when opening a new school and how this can be detrimental to low-ability students.

This paper contributes to the literature in two ways. First of all, it speaks directly to the literature on student tracking and student sorting. The main challenge in this literature is addressing the endogeneity of school choices. Indeed, student enrollment in schools may be correlated with unobserved individual, family or location characteristics.[4] To address this issue, authors use quasi-experimental shifters of school choice. For example, some studies use busing or lotteries of low-income students to high-income schools or variations in student assignments to schools.[5] While these designs are useful in pinpointing the effects of attending better schools for students benefiting from these policies, they do not speak to the effects of sorting on the entire population of students.

In this paper, I introduce a new instrument that shifts local student sorting patterns. Indeed,

[4]Such as motivation, parental involvement or distance to school.

[5]For example, Dobbie and Fryer Jr (2011) exploit a Harlem lottery system, Angrist et al. (2012) exploit a similar Massachusetts system, Banerjee et al. (2007) study an experimental intervention in India and Chetty et al. (2011) use random assignment to kindergarten classes from Project STAR.

in the Romanian high school system, the number of schools in an educational market affects the type of schools students attend, conditional on ability for the entire distribution of students. This enables me to causally estimate the effects of sorting on the entire student population. I provide credible evidence that increases in sorting exacerbate educational inequalities.

Second, the student-teacher-school spending dataset I build allows me to investigate the effects of peers, teachers and school resources on educational outcomes. Most importantly, this setup allows me to measure the relative contribution of these channels towards educational achievement. To the best of my knowledge, this is the first paper that succeeds in disentangling these channels. In particular, the finding that teacher ability is of much greater consequence than peer effects is new and has important policy implications.

In terms of peer effects, Chetty et al. (2011), Sacerdote (2001), Sacerdote (2011) and recently Patacchini et al. (2017) and Carrell et al. (2018) find significant, but typically small, peer effects on student outcomes. However, other studies, including Burke and Sass (2013) find little in the way of economically meaningful peer effects and highlight. Angrist (2014) also identifies potential identification issues that put into question some of the literature's findings. My own results suggest that peer effects are not significant for the average student. However, this masks significant heterogeneity, as relatively high-ability students benefit from better peers, while low-ability students do not.

I also contribute to the study of teacher value-added. It is found to be the main driver of student achievement differences, conditional on student ability, in several papers.[6] The effects of teacher ability on student achievement are obfuscated, however, by poor measures of teacher ability. In particular, teacher's education or experience does not seem to correlate with teacher value-added.[7] In practice, many studies avoid this issue by directly measuring teacher value-added by observing teachers who switch schools or classrooms.[8] Unfortunately, this identification strategy is plagued by the issue that teacher mobility and student school choice are most likely non-random, particularly along unobserved dimensions. The Romanian

[6]For example Rockoff (2004), Hanushek et al. (2005), Chetty et al. (2014), Petek and Pope (2016) and and Jackson (2018).

[7]For example, Dobbie and Fryer Jr (2013).

[8]For example, Rivkin et al. (2005).

data provide very rich measures of teacher ability, which allows me to directly measure teaching skills without having to resort to teacher mobility.[9] In line with the literature, I find that teacher ability is the main channel through which attending a better school impacts educational achievement.

To summarize, using very rich data on student admission and graduation records, teacher hiring and school expenditures, I analyze how student sorting affects academic performance. I find that students sort more along entrance grades in locations with more high schools, even when controlling for town population. Using the variation in sorting patterns induced by differences in high school numbers across similar-sized towns, I find that increases in sorting exacerbate educational outcome inequalities between high- and low-ability students. An analysis of high school openings confirms these findings: when a new high school opens in a small town, student sorting becomes more pronounced and the graduation score gap increases. Lastly, roughly half of the observed effects of sorting on grades can be attributed to differences in teacher ability, compared to one quarter for peer effects and a mere 5% for school expenditures.

The remainder of this paper is structured as follows. Section 2 describes the Romanian high school system and all the data sources used. Section 3 highlights student sorting and student achievement gaps prevalent in the data that serve as a motivation for the paper. Section 4 lays out the primary identification strategy and causal results linking student sorting and achievement. Section 5 analyzes the possible channels through which sorting likely impacts student scores. Lastly, section 6 provides a discussion and conclusion.

2 Setup and Data

2.1 Institutional Framework

The Romanian high school allocation system is unique and very useful for studying the consequences of school choice. In other setups, such as the US, only a limited number of jursidictions and schools allow school choice, typically in parallel to large traditional public and private school

[9] Mainly from a subject-specific exam used to assign teachers to jobs, with high scoring teachers having priority over low scoring ones. Additionally, teacher undergraduate GPA, education level and another set of exam used by teachers to advance in rank (advances in rank come with a salary increase) are also available.

systems. Even then, school choice is constrained by a number of geographic, family and/or socioeconomic and demographic conditions, or students are simply selected by schools on case by case basis. For example, charter schools, even those serving underprivilegd children, may select students and their families based on interviews, thus cherrypicking the best students and maintaining high attrition rates in order to keep only the highest-performing students. Even in the Boston public school mechanism, where students are assigned to schools via a lottery, distance to school is a criterion used to assign students to schools. The fragmented nature of these markets, their coexsitence with other, more tradiaitonal, school alternatives and the complicated selection of students into schools make it difficult, if not impossible, to asses the impact of school choice, especially across the ability distribution.

In contrast, as will be described shortly, the Romanian high school system offers an unconstrained, transparent and centralized allocation mechanism in which school choice is absolute. Moreover, since public high schools account for more than 98% of enrolment,[10] there are no concerns of selection into the school choice system and it allows the study of the consequences of school choice across the entire distribution of students. In addition, even though all schools in this setup are public, they face considerable competitive pressures to attract better students and teachers, as schools at the bottom end of the distribution that cannot fill their available seats or cannot attract teachers face pressures to merge with other schools or close down entirely. Therefore, this setup is useful for studying the competitive pressures that proponents of school choice argue can improve the eduactional system not unlike a “rising tide that lifts all boats”.

In the next paragraphs, I describe how the Romanian high school admission system works and how it presents a perfect setup to study school choice, uncontaminated by the issues highlighted previously. I was able to scrape and build a dataset of more than two million matched student admission and graduation records and match it, for the first time, to close to 40,000 scraped teacher evaluation and hiring records and to more than a million school purchases of goods and services. These allow me to explore the ways in which school choice impacts student

[10] 1.7% of high school students attended a private school in the 2017-2018 school year, according to the Romanian National Institute of Statistics.

sorting, what the impact of sorting is on student outcomes and how unequl access to teachers and resources impact the effects of school choice on students in different parts of the test score distribution.

2.1.1 High School Admissions and School Choice

Each year, Romanian middle school graduates are assigned to high schools based on a unique centralized mechanism. Each student receives an admission score. This score is based on 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 a choice of history or geography). The admission score places different weight on the two components in different years, but at least half of the score is attributed to the admission exam.

After writing the exam and receiving their admission scores, students fill out a 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. Students can choose more than a hundred preferences if they so desire, so preference truncation is not an issue. Moreover, there is no geographic restriction constraining which high schools students can express preferences over.

Students are then allocated to high schools based on a centralized algorithm. After all students submit their preference lists, they are ranked in descending order of their admission scores. Then, starting with the top-ranked student, students are assigned to their most preferred high school track that still has vacant seats. There are no other geographic, socioeconomic or family criteria that is used to assign students to schools. This mechanism ensures, first, that high-scoring students have absolute priority over lower-etrance score students and, second, that students have no incentive to strategically manipulate their preferences over tracks in hope of a better assignment.[11]

[11]In other words, the mechanism, which is equivalent to a serial dictatorship, is incentive compatible.

2.1.2 High School Graduation Exam

After completing four years of high school (grades 9-12), Romanian high school students register to take a national, standaridized high school exit exam. This exam consists of several subjects, including Romanian, mathematics, as well as other track-specific subjects. Receiving a high school diploma is contingent on passing this exam (obtaining a grade of at least 50% on all components). Morevoer, for students planning to attend postsecondary schooling, the exit exam grade exam can be used as an admission requirement. This exam is thus high stakes and is useful in comparing student abilities at high school graduation. I match the high school graduation exam data to the high school admission data to obtain more than two million student records.[12]

2.1.3 Teacher Allocation

Each year, teachers are assigned to high school teaching jobs in a way that mirrors the way students are assigned to high school seats. In order to apply for teaching jobs, prospective teachers must pass a yearly, standardized subject-specific examination that has an oral and a written component. Although the teacher allocation mechanism is slightly more complicated than the student one,[13] high-scoring teachers in general have priority over low-scoring ones in choosing the school where they work. Salaries are standardized for all teachers, so techer preferences are not infuenced by monetary considerantions.

In latter sections, I show that teachers prefer to work in schools with better students, so that teacher sorting closely mirrors student sorting. This ultimately means that schools struggling to attract high-scoring students also have to settle for low-scoring teachers, which will have implications on how school choice affects student outcomes. I was able to scrape data on close to 200,000 prospective teacher exam scores, education and other skills for a period of five years, resulting in close to 40,000 teacher job assignments across Romanian high schools.

[12] 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.

[13] Partially because 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 school.

2.1.4 School Spending

I also use school spending information in order to get at the way in which resources are allocated across schools and how these impact student performance. Since school budgets come from the central government, but also from local councils, there may be regional variations in school budgets. To get an idea of school spending, 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 was able to obtain more than one million transactions made by schools, ranging from utilities and food to classroom material and renovations.

2.1.5 Data

The data are summarized in Table 1. Since I will later use variation in the number of high schools across towns, the summary statistics are broken down by towns with different numbers of high schools. Generally speaking, the schools in one-high school towns are smaller than those in towns with more high 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 town 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 day-to-day items is similar across the different considered categories.

3 School Choices, Student Sorting and Achievement Gaps

In this section, I present several motivating empirical findings. First I show that student sorting increases in the number of high schools in a town, even after controlling for student population. Then, I relate student achievement to these sorting patterns by showing how student achievement varies across entrance score deciles by number of high schools.

Table 1: Summary of Data

Number of High Schools in Town	1	2	3	4-15	16+
Towns (Yearly)	349.8 (29.4)	54.1 (1.4)	25.6 (2.2)	54.1 (1.5)	19.3 (0.5)
Tracks (per School)	1.5 (1.2)	1.7 (1.4)	1.8 (1.6)	1.8 (1.5)	1.7 (1.3)
Admitted Students (Total)	329,254	160,755	126,640	755,450	543,825
Yearly Admitted Students (per Town)	76 (72)	231 (128)	369 (231)	977 (742)	3125 (3,121)
Yearly Admitted Students (per School)	76 (72)	115 (75)	123 (93)	133 (105)	114 (82)
Entrance Score (Percentile)	38 (26)	48 (27)	50 (28)	52 (29)	56 (29)
Exit Exam Students (Total)	337,442	153,905	122,532	624,363	893,506
Exit Exam Pass Rate	0.49	0.60	0.64	0.64	0.65
Yearly Exit Exam Students (per Town)	79 (79)	237 (131)	399 (186)	961 (555)	3851 (3831)
Yearly Exit Exam Students (per School)	79 (79)	119 (80)	133 (88)	133 (85)	135 (96)
Exit Exam Score (Percentile)	41 (27)	48 (28)	51 (28)	52 (29)	52 (29)
Hired Teachers (Total)	5,050	1,680	969	5,339	6,957
Yearly Hired Teachers (per Town)	3.1 (2.1)	6.3 (3.4)	9.1 (3.9)	21.8 (15.1)	133.8 (175.0)
Yearly Hired Teachers (per School)	3.1 (2.1)	3.1 (2.1)	3.0 (2.0)	3.0 (2.3)	4.5 (3.4)
Teacher Score (Percentile)	47 (28)	47 (28)	49 (28)	49 (29)	54 (29)
Total Town Spending (EUR 000s)	79 (556)	154 (1025)	98 (108)	359 (1231)	2,418 (2975)
Total School Spending (EUR 000s)	79 (556)	92 (724)	37 (62)	56 (477)	91 (371)
Spending per Student (Town)	533 (5,337)	950 (11,468)	199 (351)	548 (2,639)	1,774 (4,905)
Direct Spending per Student (Town)	461 (5,453)	681 (12,118)	128 (308)	482 (133)	250 (4,905)

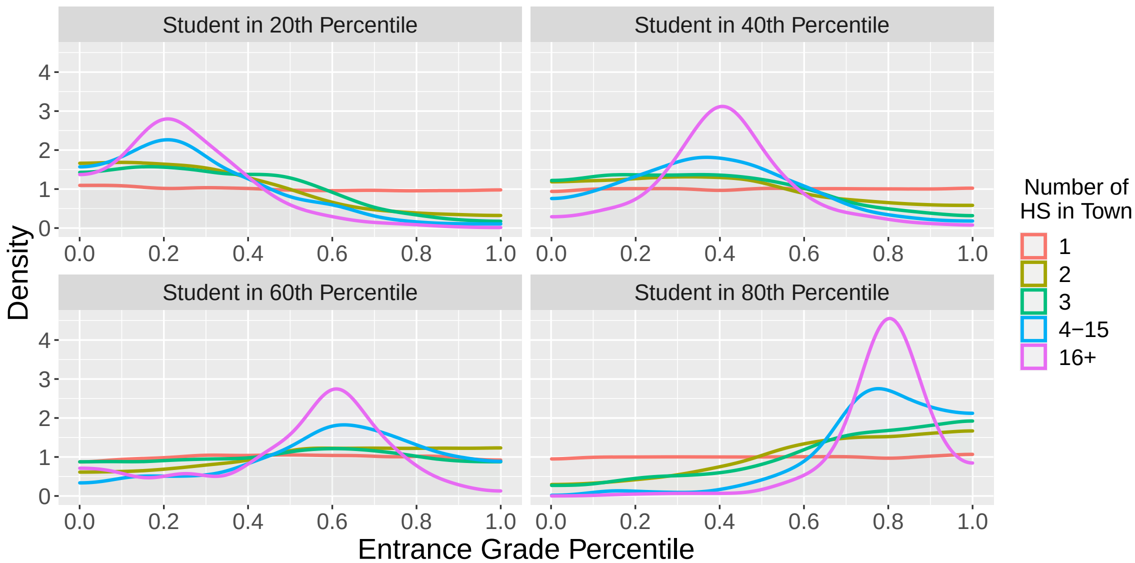
Note: This table contains summary statistics of the admission, graduation, teacher and spending records. The values in the table are, unless otherwise specified, means, with standard deviations between parentheses. School closures and openings mean that the number of towns in each category changes from year to year. Entrance, 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).

I find that the more high schools there are in a town, the larger the achievement gap between top and bottom entrance score students within that town. The largest increase in this achievement gap is registered between towns with one high school and towns with two high schools. This suggests that the results are indeed driven by sorting pattern differences (which are largest between these two types of towns) rather than by any town size effect.

Across towns, high entrance score students in towns with more high schools outperform their counterparts in towns with few high schools. At the other end of the distribution, low entrance score students in areas with few high schools surprisingly outperform their urban counterparts. These results are consistent with sorting exacerbating educational inequalities between high-ability and low-ability students.

3.1 Student Sorting

Figure 1: Sorting Patterns by Town Size (School Level)

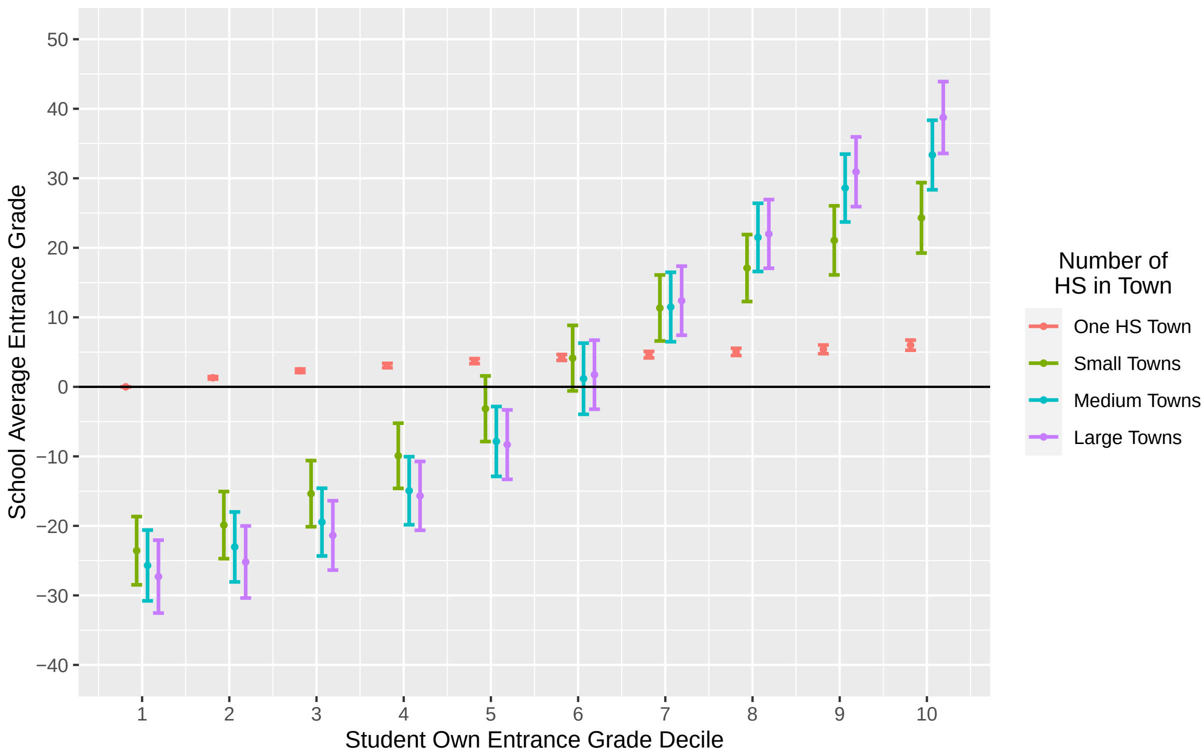


Note: This figure plots the distribution of within-school peer entrance scores (computed as percentile scores at the town-year level), conditional on own entrance score and number of high schools in town. I use kernel density estimators with boundary corrections.

I now describe the student sorting patterns. First, the typical distribution of high school peers of a student varies with the number of high schools in their town and their entrance score percentile within their town and cohort in Figure 1.

For example, consider a hypothetical student A, whose entrance score ranked in the twentieth percentile in their town. The first panel of the figure shows the typical distribution of high school level peers of student A and how it varies with the number of high schools in a town. In towns with one high school, the peer distribution is flat, meaning that the entire town's entrance grade distribution is represented. As the number of high schools increases, student A faces more competition when applying to a good school. Given their poor entrance score, they will only be able to gain admission to a poor quality schools, attended by other students with low entrance scores.

Figure 2: Student vs High School Peer Entrance Grades



Note: This figure shows the relationship between student own high school entrance score and average peer entrance within the same high school, and how this relationship varies by town size and student entrance score. Specifically, it plots $\delta_d + \delta_n + \delta_{d\times n}$ for different combinations of d and n in equation 1. Small Towns have 2-6 HS, Medium Towns have 7-15 HS, Large Towns have 16+ HS.

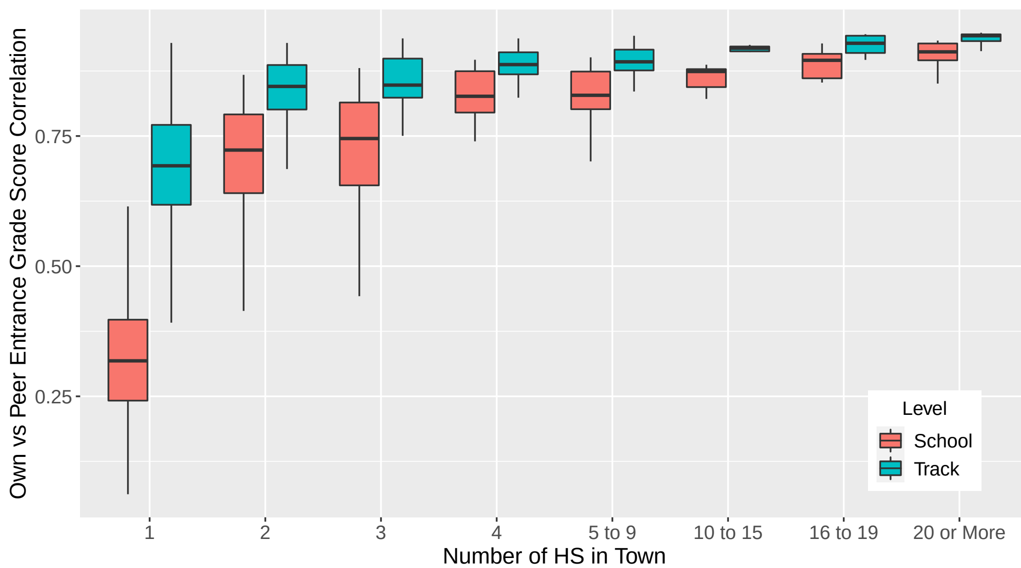
At the other end of the spectrum, in the last panel of Figure 1, I plot the typical high school peer distribution of student B, whose entrance score ranked in the eightieth percentile within their town. In a one high school town, B's typical peers will be no different than A's, as all students attend the same high school. However, in towns with more high schools, B's high entrance score will enable them to gain admission to a more selective school, where their peers will also have high entrance grades.

Next, to get a more tangible sense of the extent to which students sort into high schools, I regress student entrance scores on average entrance scores within their schools. I also interact student ability with number of high schools to capture how peer entrance scores vary by student entrance score, number of high schools in town of attendance and town population. Specifically, I estimate the following model, which should capture differences in peer scores across student ability and town characteristics:

$$\mu^e_{-ihy} = \beta_0 + \delta_d + \delta_n + \delta_{d\times n} + \delta_y + \delta_p + \delta_l + \epsilon_i \quad (1)$$

where μ^e_{hy} is the high school entrance score mean in high school h and year y and I use the following fixed effects: entrance score decile of student i within their cohort, nationally (δ_d), number of high schools in town l where student attends high school (δ_n), the interaction between number of high school and student entrance decile ($\delta_{d\times n}$), year (δ_y), type of high school track or program (δ_p) and town or location (δ_l). The results are presented in Table 9 of the Appendix and illustrated in Figure 2.

Figure 3: Across- and Within-School Student Sorting



Note: This figure shows the distribution of the correlations between own admission scores and peer scores (within tracks and within schools), across towns with different numbers of high schools.

Students in the highest decile in large towns attend schools with average entrance scores that are 33 percentiles higher than their one high school town counterparts. At the other end of the spectrum, students with bottom decile entrance scores in cities attend schools where the average entrance grade is 27 percentiles lower than their rural counterparts. In large cities, the average entrance score difference between the typical school attended by high-ability students and those attended by low-ability students is 66 percentiles. In one high school towns, this difference shrinks to a mere 6 percentiles.[14]

In terms of between-school and within-school sorting, the advantage of the Romanian high school admission system is that students apply directly to tracks, so within-school sorting is transparent. Figure 3 illustrates the correlation patterns between students and their peers' entrance scores, at the high school and high school-track levels and how these vary across towns with different numbers of high schools. In Appendix C, I show that student sorting occurs principally at high school level, rather than at the track or classroom level. Even in towns with few high schools, between-track sorting is limited and does not make up for students having limited high school choices.

3.2 Achievement Gaps

To examine the achievement gaps and how they vary by number of high schools across towns, I project high school graduation grads on entrance grades and the number of high schools in the town of high school attendance. This specification also interacts student entrance score deciles with the number of high schools. This captures differences in how similar-ability students perform at graduation across locations with different numbers of high schools.

$$g_i = \beta_0 + \beta_e e_i + \delta_d + \delta_n + \delta_m + \delta_p + \delta_y + \delta_s + \delta_{d\times n} + \delta_{d\times s} + \epsilon_i \tag{2}$$

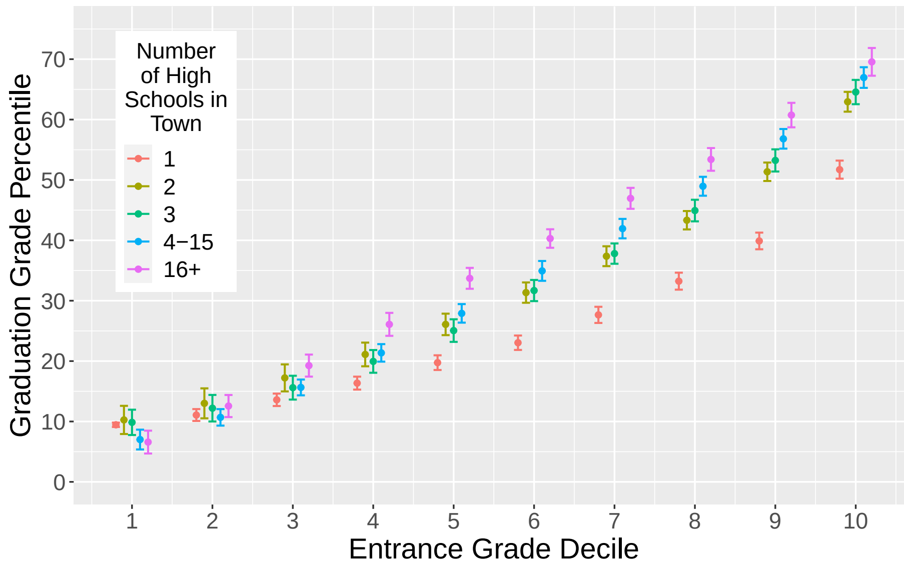
Here, g_i is the high school graduation percentile of student i who attended middle school m, and high school program (or track) p of high school h, in location (town) l and cohort y and e_i is the high school entrance percentile of student i. Deltas denote fixed effects. I include the following: δ_n (number of high schools in location or town l and year y), d (entrance grade decile of student i at the town-cohort level), δ_y (year), δ_m (middle school), δ_p (high school program or track), δ_s (number of students entering high school in town l and year y) and the interaction terms $\delta_{d\times n}$ and $\delta_{d\times s}$.

The full set of estimation results of equation 2 are reported in Table 8 in the Appendix. Different columns of the table represent different numbers of fixed effects controlled for. The

[14] This difference is zero within towns, as no sorting happens, but non-zero overall because different one-high school towns have different compositions of student entrance scores. High-entrance score students in one-high school towns are more likely to attend schools in towns with better peers than their low-entrance score counterparts.

baseline model has a full set of fixed effects, except town fixed effects (column (6)). Given that the many interaction terms in this model, I graph out students' predicted graduation scores based on their entrance scores and the number of high schools in their town based on the regression results (Figure 4).

Figure 4: Predicted Graduation Percentile by Town Size and Entrance Decile



Note: This figure plots the expected graduation percentile using the town size, entrance decile (within town cohort) and their interaction, i.e. $\delta_d + \delta_n + \delta_{d\times n}$ from equation 2. I also use a student's expected entrance percentile conditional on their town size and entrance grade decile (i.e. $\beta_e \mathbb{E}[e_i | d_{ly}(e_i), n_{ly}]$) so that the estimates are not driven by differences in entrance grade within deciles across towns with different numbers of high schools. I plot the 95% confidence interval bounds.

The regression results show that, first, the graduation score gap between students in many-high school towns and those of similar ability in few-high school towns is increasing in entrance scores. For example, students whose entrance score is in the top decile in towns with more than 15 high schools score, on average, 16 percentiles higher on the graduation exam than their counterparts in towns with only one high school. Second, at the other end of the spectrum, students who entered high school in the bottom decile in many-high school towns score 3 percentiles lower on the graduation exam than similar students in one high school towns. Third, the graduation gap between high- and low-ability students within towns increases in the number of high schools. While the graduation gap between students who scored in the highest decile (nationally) on the entrance exam and those who scored in the bottom decile is 42 percentiles in one high school towns, this figure is 63 percentiles in cities.

The reader should note that the graduation gaps described here vary with the number of schools even though I include an interaction term between student ability and the number of students in a town. This specification thus addresses the concern that these graduation gaps occur because of different socioeconomic inequality levels, for example, between students living in large towns and students living in smaller towns. There is a strong sense that even conditional on town population or student population, the number of schools in a town is crucial in explaining the graduation gap.

Moreover, the results indicate that the largest differences in graduation score gaps do not occur between students in large, many-high school towns and very small, few-high school towns. Instead, the largest differences in graduation gaps across ability occur between towns with one high school and towns with two high schools. This is true even though the differences in these towns' populations and socioeconomic characteristics are plausibly much smaller than between, say, towns with two high schools and large cities. These differences in graduation gaps are mainly driven by differences in the number of high schools rather than by differences in town size.

One of this paper's main objectives is to explain why graduation score gaps follow the patterns described above. I hypothesize that, given the competitive admission system in Romania, different numbers of schools across locations mechanically give rise to starkly different student sorting patterns. These sorting patterns are ultimately responsible for the observed graduation gaps.

The intuition is that, in one high schools towns, sorting along ability is impossible.[15] All the students in these towns attend the same high school and their peers have entrance scores from all across the entrance grade distribution. On the other hand, in towns with two high schools, students can sort along ability. To the extent that some consensus exists about which school is more desirable and given that high entrance score students receive priority, one would expect to see a large degree of sorting along entrance grades. Looking at towns with higher number of

[15] Except for migrating to a town with more high schools, which is costly and uncommon in the data. Moreover, in an alternate specification, I define education markets endogenously based on migration patterns in order to alleviate this issue. I also exclude students who migrate between these markets.

high schools, the potential for sorting is even greater. Still, the largest increase in the potential for sorting is between towns with one high school and towns with two high schools.

Sorting may affect graduation grades and give rise to the graduation gaps observed in the data in several ways. High-ability students may sort into schools with higher-ability peers and teachers or more teaching resources. I will explore the potential channels through which sorting affects graduation grades in a latter section.

If sorting does indeed affect student outcomes, the graduation gaps documented here are precisely the types of patterns one would expect to find. High-ability students in cities can attend selective schools, while their low-ability counterparts can only attend poor-quality schools, which exacerbates inequalities between these two groups. On the other hand, in rural areas, there is relatively little sorting. low-ability students in these areas benefit compared to their urban counterparts. Meanwhile, high-ability students in rural areas cannot sort into good schools and ultimately lag behind their urban peers.

To summarize, peer composition varies significantly across towns with different numbers of high schools. While in one high school towns, peer ability is uncorrelated with own ability, this correlation is extremely strong in urban, many-high school areas, as students of similar abilities tend to cluster in the same schools. High-ability students in urban areas sort into very selective schools, while their rural counterparts cannot do so. Low-ability urban students face very stiff competition and can only gain admission to high schools attended by other low entrance score students. Sorting primarily takes place at the high school level. In places with few high schools, the absence of high school sorting is only minimally offset by sorting at the track level.

4 Identification Strategy and Main Results: Causal Effect of Sorting on Graduation Scores

The previous section has shown that locations with more student sorting experience higher student achievement gaps. I also showed that patterns in achievement gaps across locations closely mirror student sorting patterns.

In this section, I lay out two estimation strategies that establish a causal link between student sorting along ability and student performance. I first use variation in sorting patterns across towns brought about by the different high school numbers across towns in an instrumental variable framework. Secondly, I deploy triple difference framework to analyze the disruption in preexisting sorting patterns caused by school openings in towns with few high schools.

4.1 Causal Effect of Sorting on Grades at Graduation

4.1.1 Using Variation in Number of Schools (IV)

The model I first exploit in order to asses the impact of sorting on graduation grades is a variation of the Manski (1993) peer effects model:

$$g_i = \beta_0 + \beta_e e_i + \beta_\mu \mu^e_{\text{-ihy}} + \delta_n + \delta_d + \delta_l + \delta_m + \delta_p + \delta_y + \delta_s + \delta_{s\times d} + \epsilon_i \tag{3}$$

Here, g_i is the student percentile on the high school graduation exam, e_i is the student percentile on the high school entrance exam and μ_{-ihy} is the mean entrance grade in high school h and year y (excluding student i). I include fixed effects denoted with δ. These include the following fixed effects: δ_n (number of high schools in town), δ_d (entrance grade decile at the town-cohort level), δ_l (town), δ_m (middle school), δ_p (high school track or program), δ_y (year), δ_s (the number of students entering high schools in town l and year y) and interaction $\delta_{s\times d}$. Typically, this model is used when estimating peer effects when group formation is random. In this paper, the interpretation will be different.

In this specification, the variable μ_{-ihy} will be used a proxy for school quality and not a peer effect estimate. I assume that students are rational and seek admittance to good schools when given the choice. Good schools may be defined by higher-scoring students or teachers, better management or better learning resources, but, for the moment, I do not yet take a stand on what exactly school quality means. Simply, I assume that, on average, schools that are able to attract higher entrance score students are of higher quality than those with low-entrance score students.

A more immediate concern is that in the Romanian high school setup, μ_{-ihy} is endogenous, as it results from a student choice. Endogeneity could be modeled as an omitted variable that is correlated with the peer entrance scores. I model the error term in equation 3, as:

$$\epsilon_i = \zeta f_i + \chi_i \tag{4}$$

where f_i are unobservable characteristics of individual i that impact high school performance and is correlated with μ_{-ihy}. One example of this is the motivation to attend university. Conditional on entrance score, this may drive a student to seek a higher quality school, while also impacting their motivation to perform well in school. This would bias the estimates of β_μ upward and overstate the importance of school quality on the graduation exam grade. The instrument I use to address this issue is an interaction between the number of schools in the student's town and their ranking within the town,[16] so that the first stage of the estimation is:[17]

$$\mu^e_{hy} = \gamma_0 + \gamma_e e_i + \eta_n + \eta_d + \boldsymbol{\eta_{d\times n}} + \eta_m + \eta_l + \eta_p + \eta_y + \eta_s + \eta_{s\times d} + \xi_i \tag{5}$$

The intuition follows. This instrument exploits variation in the number of high schools across locations of similar populations. In places with more high schools, there is more potential for sorting across schools, and high-ability students will, on average, attend a better (or high-entrance score) high school. In contrast, low-ability students will attend worse (low-entrance score) schools in locations with more high schools, ceteris paribus, as seen in Figure 4.

For example, Figure 5 illustrates how, high-entrance grade students are able to sort into more selective high schools, on average, than their counterparts in towns with similar populations, but fewer high schools. At the other end of the spectrum, low-entrance grade students are relegated to less selective high schools in tows with more high schools.

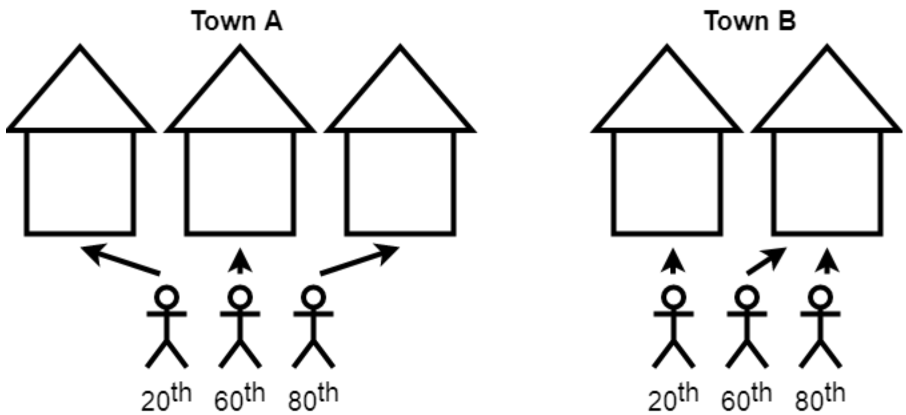
Secondly, this instrument satisfies the exclusion restriction. In other words, for students with the same entrance scores and attending high school in towns with the same number of high schools, their in-town ranking and size of their town is plausibly uncorrelated with their motivation or other personal characteristics which may affect their scores at graduation. More formally, $\eta_{d\times n}$ is conditionally independent of f_i and χ_i.

Another identifying assumption is that the number of high schools across locations of sim-

[16] i.e. $d_{ly}(e_i) \times n_l$, abbreviated as $d \times n$ for notational simplicity.

[17] Where the η variables represent fixed effects, in order to avoid confusion with the δ fixed effects in the second stage.

Figure 5: Instrumental Variable: An Illustration



Note: This figure illustrates the way in which the instrument shifts the type of school students attend. In locations with more high schools (town A), high-entrance score students attend, on average, a more selective school than their counterparts in a similar-sized towns with fewer high school (town B). Low-entrance score students in towns with more high schools (A) are relegated to less selective schools than in locations with fewer high schools (B).

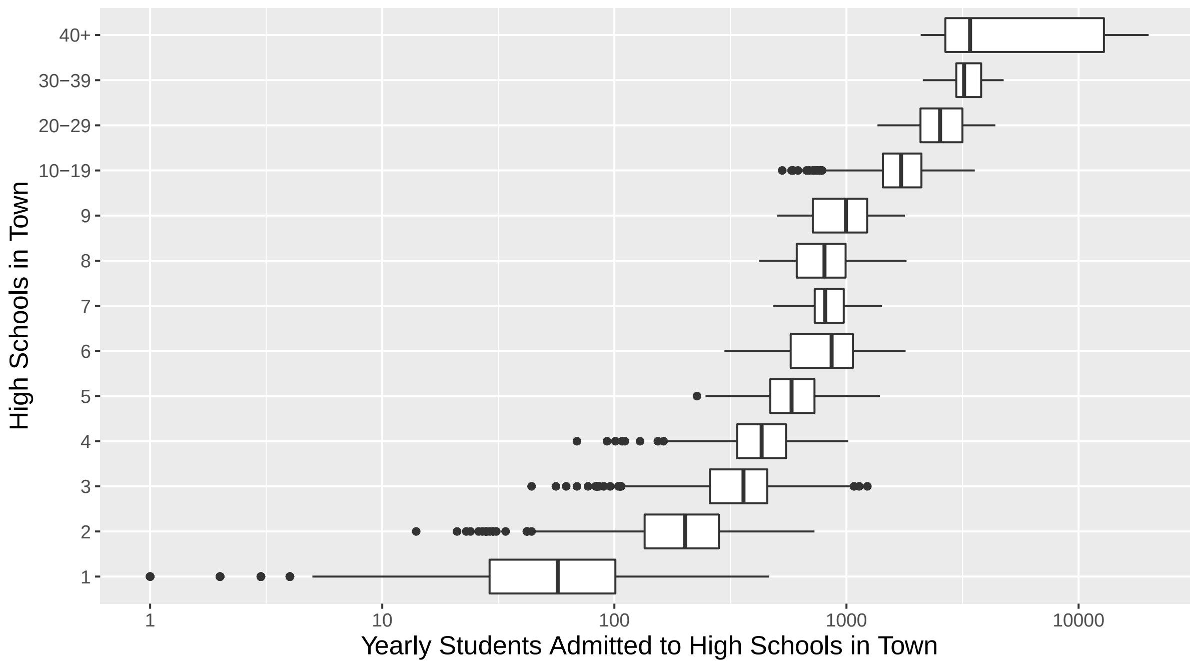
ilar sizes affects students grades only through the type of schools that students attend. In other words, I assume that the number of high schools across locations of similar populations is not correlated with other non-observable town-level characteristics that affect high school performance gaps between high- and low-ability students.

One observation that alleviates this type of concern is related to school closures. Romania underwent massive depopulation since the fall of the communist regime in 1989, affecting towns heterogenously. However, school closures are extremely rare. Thus, there is a sense that the number of high schools in a given town is determined by decades-old decisions that are divorced from that town's current economic, social and demographic realities and is very unlikely to be systematically correlated with student performance gaps.

Figure 6 shows that there is significant overlap in number of high schools across towns with similar incoming high school student populations. This variation is precisely the one captured by the instrumental variable. Notice that this variation implies that school sizes across these locations differ. However, classroom sizes are fixed at 28 students, typically and, since most schools are oversubscribed, there variation in classroom size is not a major concern.

Lastly, for now, I assume that the effect of attending a better school on student performance

Figure 6: Number of Students vs Number of High Schools Across Towns



Note: This figure plots the distribution of the number of students admitted to high schools across towns with different numbers of high schools. Notice that, while the number of admitted students is increasing in the number of high schools, there is significant overlap in the number of students across towns with different numbers of high schools.

is homogeneous for all students. This assumption will be relaxed later, when I study the channels through which sorting affects student scores.

Several identification challenges, including sample selection and student migration issues, are addressed later in the section. I conduct appropriate robustness checks in order to alleviate concerns regarding them.

First Stage I estimate equation 3, using the interaction between student entrance score decile (at the town-cohort level) and the number of high schools in the student's town as an instrument for the ability of his or her peers at the school (μ_{-ihy}) and at the school-track levels (μ_{-ihpy}). As explained previously, the peer means and their corresponding estimates should not be interpreted as peer effects. Rather, they are proxies for school (or track) quality and may capture superior teaching and school facilities, as well as peer effects.

Figure 7 and Table 10 (Table 11) in the Appendix present the first stage estimates at the school (track) levels. The differences in sorting on entrance grades across towns with different numbers of high schools are substantial. On average, lowest entrance grade decile students' peers in one high school towns score 29 (15) percentiles higher than their counterparts in many-high school towns. At the other end of the spectrum, highest entrance grade decile students' peers in one high school towns score 28 (19) percentiles lower at high school entrance than their counterparts in towns with at least 15 high schools.

F-statistics for weak instrument tests are computed for the first stages. All F-statistics are extremely large and rule out weak instruments beyond any doubt. The F-statistics for school (track) first stages are all larger than 297 (378). These far exceed the threshold derived by Stock and Yogo (2002) for a maximum bias of 0.05.[18] Moreover, these also exceed the more conservative threshold of 104.7 recently developed by Lee et al. (2020).[19]

The first stage results suggest that sorting intensity within schools and tracks increases rapidly in the number of high schools in a town, even when controlling for student population. Intuitively, the instrumental variable picks up variation in the average peer entrance score of students who have similar abilities and live in towns with similar student populations, but with different numbers of high schools. This difference in sorting patterns is especially stark between towns with one high school and towns with two high schools. For example, a high entrance score student in a two high school town will typically attend the high school in their town with a higher average entrance score. In contrast, an identical student in a similar-size town that only has one high school will not be able to select into a high entrance grade high school.[20] Thus, the average entrance score of this student's peers will be significantly lower than that of two-high school town counterpart.

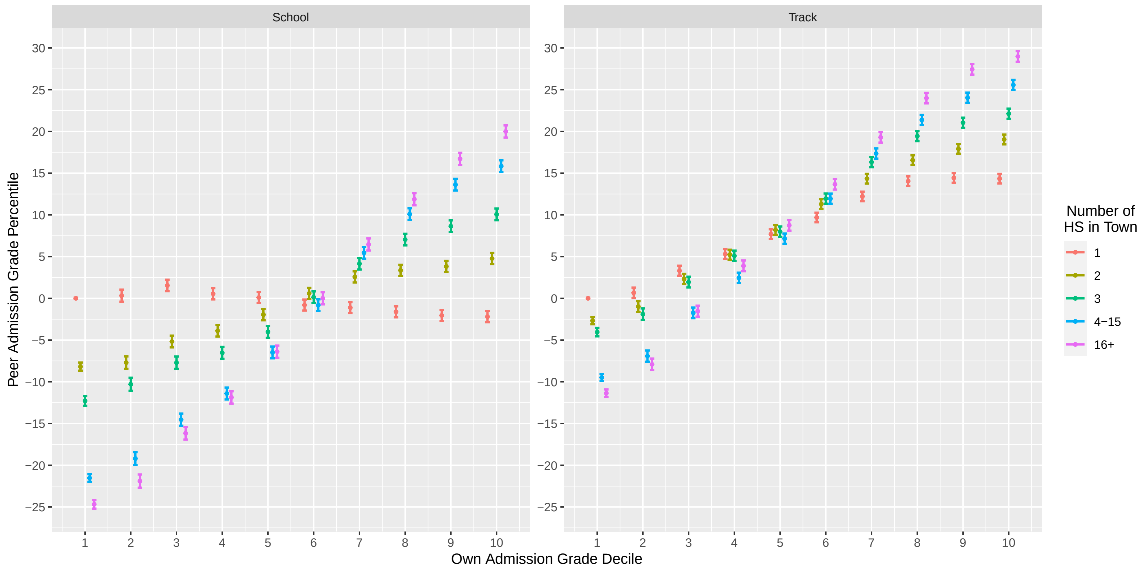
To summarize, conditional on town population, I find that the ability of peers is increasing both in own ability and in the number of high schools in the town for students who are above-average. The competitive admission system works in their advantage and they are able to sort into selective schools. For below-average student, average peer entrance score is increasing

[18]This stands at approximaetly 21.4 for 40 instruments and one endogenous variable.

[19]Intuitively, Lee et al. (2020) find that unless the first stage F-statistic is at least 104.7, the true confidence intervals of the second stage estimate of the β on the endogenous variable should be constructed using t-values larger than 1.96. In my setup, this is can be dismissed out of hand, since the F-statistics all far exceed this threshold.

[20]That is, without migrating to a different town. Migration is addressed later in this section.

Figure 7: IV First Stage: Predicted Mean Peer Entrance Grade by Own Entrance Grade Decile and Number of High Schools in Town



Note: This figure plots the expected mean entrance percentile of a student's peers conditional on his or her entrance grade decile and number of high schools in the town of high school attendance, i.e. $\gamma_{n_l} n_l + \gamma_d d_y(e_i) + \gamma_{d,n}(n_l \times d_y(e_i))$ from equation 5. I also use a student's expected entrance percentile conditional on the number of high schools in their town and entrance grade decile (i.e. $\gamma_e \mathbb{E}[e_i|d_y(e_i), n_l]$) so that the estimates are not driven by differences in entrance grade within deciles across towns of different sizes or numbers of high schools. I exclude town fixed effects and plot the 95% confidence intervals.

in own entrance score, but decreasing in number of high schools. This reflects the fact that low-ability students are relegated to low-quality schools in towns with more schools, due to competition.

Second Stage Table 2 presents the second stage estimates.[21] The baseline model, which includes fixed effects for town, year, town-cohort admission score decile, track and middle school and controls for town student population and numbers of high schools across towns indicates that attending a high school (track) with a 1 percentile higher mean entrance score increases a student's graduation score by 0.16 (0.30) percentiles.

Effect of Sorting on Graduation Gaps I now turn to the following question: given the sorting patterns observed in Romanian towns, how much does student sorting contribute to graduation score gaps? More specifically, I use the IV estimates to predict a student's expected

[21] Table 26 (Table 13) presents different specifications of the second stage results at the school (track) level.

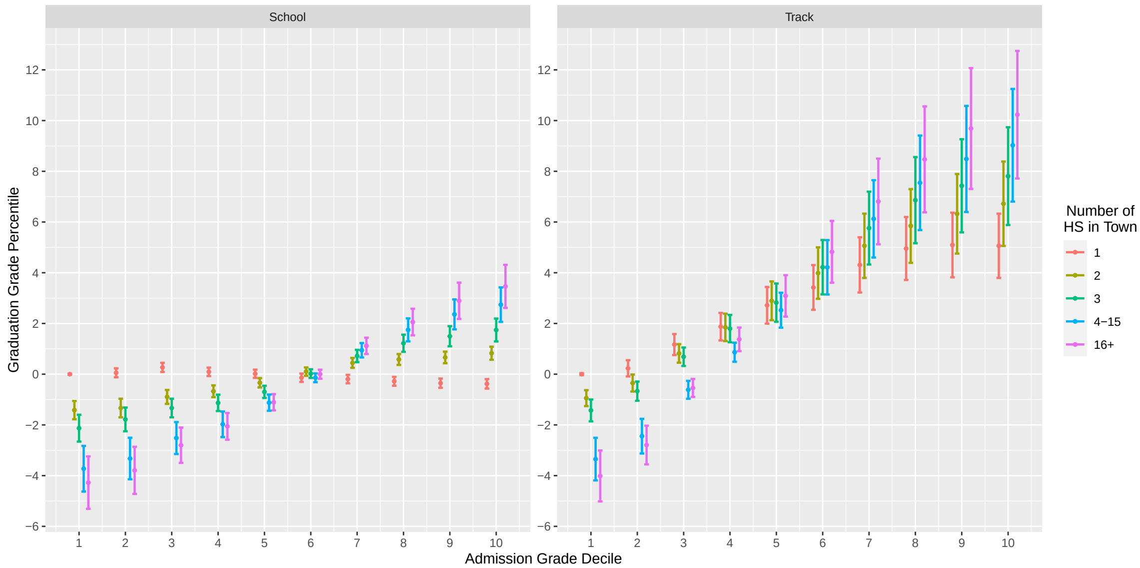
Table 2: IV Second Stage

	Dependent variable:	
	Graduation Score Percentile	
	School Level	Track Level
	(1)	(2)
Admission Score (Percentile)	0.530***	0.454***
Instrumented Peer Admission Score (Percentile)	0.173***	0.353***
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	544	544
Year FE	12	12
Track FE	190	190
MS FE	18,590	18,590
Observations	1,161,051	1,161,051
Adjusted R^2	0.638	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 3. 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 and track levels) 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.

graduation score, given their entrance score and the number of schools in the town where they attend high school. In this way, it is possible to quantify the expected graduation score gap engendered by sorting at the school or track level. For example, I estimate the quality of a school attended by a high-ability student in many-high school towns using the first stage estimates and how attending this type of school will affect their graduation grades. Given that high-ability students in many-high school towns can sort into very selective schools, the expected effect on the graduation grade for this type of student, who can sort into a good school, should be

Figure 8: Predicted Mean Causal Effect of Sorting



Note: This figure plots the expected mean causal effect of sorting on graduation grade, by entrance grade decile and number of high schools in the town of high school attendance. This is computed as $\beta_\mu \mathbb{E}[\hat{\mu}^e_{\text{hy}} | d_{ly}(e_i), n_l]]$. I also plot the 95% confidence intervals.

positive. This contrasts with students of similar ability in few-high school towns, who will lack the option of attending selective schools.

Specifically, I first use the first stage estimates to predict, based on student entrance score and town they attend high school in, the school quality they attend.[22] Then, given this estimate of school quality, I use the second stage estimates to predict the estimated effect of sorting on their grade at graduation.[23] Note that, alternatively, I could have used the second stage estimates directly with the realized school quality (μ_{-ihy}) rather than using estimated school quality ($\hat{\mu}_{-ihy}$). However, given that school quality is endogenous, this would lead to a biased estimate.[24] I plot this estimate and corresponding confidence intervals for students in different entrance deciles and attending high school in towns with different numbers of high schools.

I find that students in the sixth decile or above benefit from attending a high school (high school track) in many-high school towns and this benefit increases in both in the number of high

[22] I compute $\hat{\mu}_{-ihy} = \gamma_{n_l} n_{ly} + \gamma_d d_{ly}(e_i) + \gamma_{d,n}(n_{ly} \times d_{ly}(e_i)) + \gamma_e \mathbb{E}[e_i | d_{ly}, n_{ly}]$ from equation 5.

[23] More specifically, I compute $\beta_\mu \hat{\mu}_{-ihy}$

[24] For example, if, conditional on entrance scores, more motivated students perform better in high school and also tend to enroll into better schools, using this approach would lead to results that are upward biased. Indeed, this approach would capture the effect of attending a better school via sorting, but also the effect of having higher motivation.

schools and student entrance score. On the other hand, students in the third decile or lower in their town are better off attending high school in towns with fewer high schools. It turns out that in cities, students in the top entrance grade decile receive a 7 (12) percentile boost on their graduation grade from sorting, on average.[25] This is in contrast to the 3 (7) percentile increase seen by their high-ability counterparts in one high school towns, who are penalized by not being able to choose more selective high schools. At the other end of the spectrum, students in the lowest entrance grade decile who attend high school in large cities receive a 4 (4) graduation grade percentile penalty from sorting when compared to their counterparts in one high school towns.

Moreover, in large cities, the high levels of sorting at the school (track) levels lead to a 12 (17) percentile widening of the performance gap between top entrance score decile students and their counterparts in the lowest decile. In towns with only one high school, this figure shrinks to 3 (7) percentiles.

Significantly, these result is not driven by students with similar admission scores performing differently in towns of different populations. By controlling for student population in towns and interacting it with individual student admission scores, the model allows students with similar admission scores living in towns with different populations to have different graduation scores. The identifying variation is thus variation in graduation grades of students of similar abilities across towns with similar populations, but different numbers of high schools.

To summarize, increasing levels of sorting are accountable for a widening in graduation score gaps between high- and low-ability students within towns. Second, sorting widens the performance gap between urban high-ability students (who can attend selective schools) and rural high-ability students (who cannot). The gap between low-ability urban students (who attend the worst urban schools) and low-ability rural students (who benefit from low sorting in rural areas) shrinks via sorting.

[25]Compared to the baseline case of students in the lowest decile in one high school towns.

4.1.2 Using School Openings (Triple Difference)

I now turn to the analysis of 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 prefer to enroll in the high school perceived to be better.[26] The competitive nature of the admissions system will allow high entrance score students to attend the good school, while students with relatively low entrance grades are relegated to the lower quality school.

Moreover, while I do not have specific information on the determinants of schools opening in some towns versus others, the timing of these openings is plausibly exogenous. In fact, construction delays are very common in Romania, especially in the public sector. For new schools, projects are often a coordinated effort between the Education Ministry, county-level government and local government, which can be complicated and time consuming. To make matters worse, elections at the local level and the national level are staggered, so a shifting political landscape complicates the planning of long-term projects. Lastly, there is evidence that local budgets in Romania are affected by politics, with regional political "barons" controlling the purse-strings at the county-level. The central government has also been accused of inflating the budgets of regions or towns governed by its own mayors. In this environment, it is unlikely that school openings and their timing are the result of an objective, long-term education policy plan and the time between the decision to open a new school and the school opening is probably long.

Even when a new school building is not necessary,[27] it is difficult to hire the personnel quickly, especially since public servants must be hired through a transparent and competitive process. Additionally, it takes four years from the time a high school is opened until the first cohort graduates from high school.

[26] At this point, I do not take a stand on what makes a school better than another. This can plausibly result from having more qualified teachers, offering better facilities and educational tracks and attracting better students, among other things.

[27] For example, a middle school may be converted into a high school

I use a triple difference (DDD) approach to compare the differences in graduation grades of high entrance score students versus low entrance score students, in towns of where a new school was opened versus towns with no new schools, before and after the school opening. Since schools open in different years for different towns, it is impossible to define a before and after opening period. Following Wooldridge (2002), I adopt the standard approach of staggered DDD, including time dummies, town dummies and all pairwise interactions with the quartiles. The equation I estimate is:

$$g_i = \beta_0 + \beta_e e_i + \beta_T \mathrm{T} + \delta_q + \delta_l + \delta_y + \delta_{qy} + \delta_{lq} + \delta_s + \eta_{s\times q} + \boldsymbol{\delta_{Tq}} + \epsilon_i \tag{6}$$

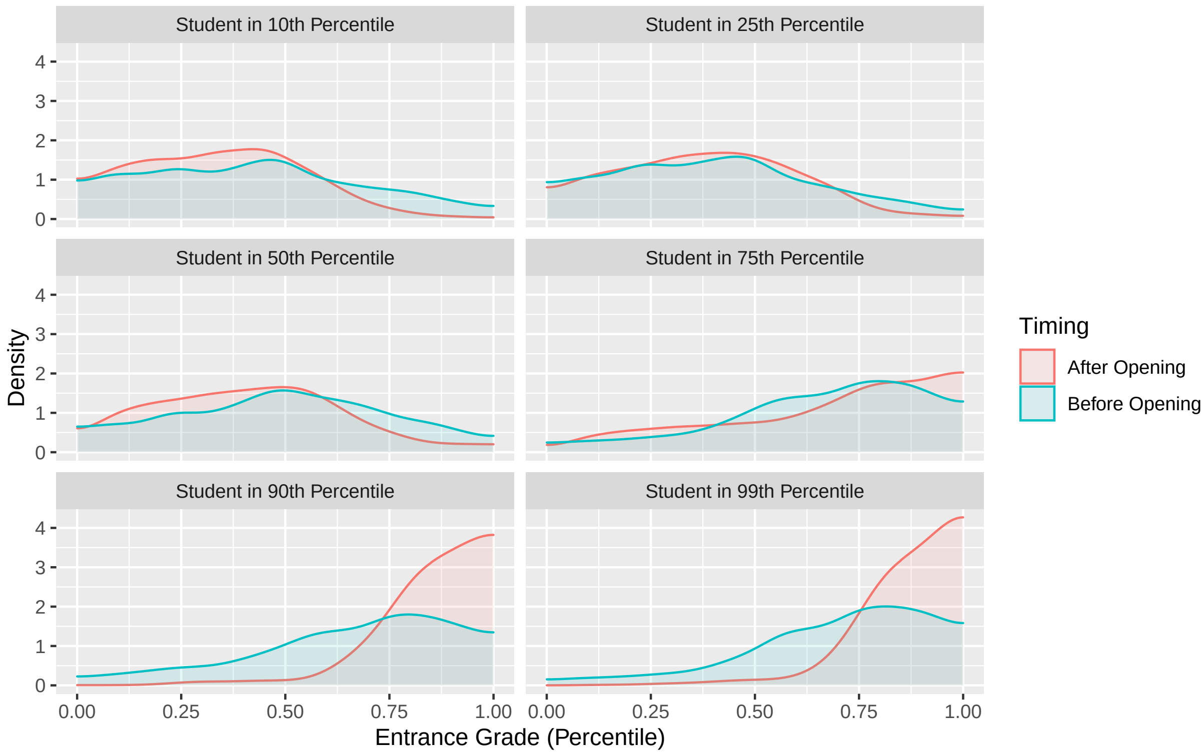
Here, g_i is the student percentile on the high school graduation exam, e_i is the student entrance grade percentile and fixed effects are denoted by δ. These include: the entrance grade quartile within town-year of student i (δ_q), town (δ_l), year (δ_y), quartile-year (δ_{qy}), town-quartile (δ_{lq}), number of students in a town in a cohort (δ_s), number of students in the town-cohort interacted with a student's entrance grade quartile ($\delta_{q\times s}$) and treatment-year (δ_{Ty}) . I also include T_{ly} (the treatment variable, abbreviated T), a dummy variable indicating whether or not town l was subject to a school opening before or during year y. It is non-zero only for treated towns after a new school opens. Note that the inclusion of the interaction term $\delta_{q\times s}$ means that the model is flexible, allowing students with similar entrance grades to perform differently in towns with different populations.

An alternate specification, using the relative number of seats in the opening high school relative to the town's preexisting seats as a treatment variable, instead of a simple treatment dummy, is estimated and results are presented in the Appendix (Table 14).[28]

For this estimation, I restrict my attention to towns with either one or two high schools in the pre-period. Indeed, the opening of one high school in many-high school towns is unlikely to disrupt the preexisting sorting patterns in that town sufficiently. Moreover, I exclude the

[28] In this alternative specification, the treatment variable T and it is computed as the number of seats in a newly-opened school relative to the number of seats in the old schools of that town. For example, if a town l has 1,000 seats and a new school with 100 seats opens in year y, T will take a value of 0.1 for town l and any year including and after y. It will take a value of zero for any town before a new school is built and for any town in which there are no school openings. The DDD coefficient of interest is δ_{Tq}. It captures how the the difference in graduation scores between students in different entrance score quartiles evolves after a school opening in a town versus before the opening compared to towns where there was no school opening.

Figure 9: DDD: Sorting Patterns Before and After School Opening (Treatment Group), by Entrance Score



Note: This figure plots the distribution of student peers (within the same school) in the treatment group, conditional on own entrance score, before and after high school opening.

openings of schools that are not suitable substitutes for preexisting schools (e.g. religious high schools[29] and high schools where teaching is conducted in a foreign language[30]) and schools that already existed in a different form (e.g. vocational or other type of schools and were changed into high schools). Table 15 of Appendix A provides more information on the school openings retained for this analysis.

The triple difference results follow. As noted previously, this approach exploits disturbances in sorting patterns caused by school openings in few-high school towns. Figures 9 and 13 in the Appendix show the changes in sorting patterns before and after high school openings in the treatment and control groups, respectively. The control group shows very little change over time in the distribution of peers conditional on entrance score. In contrast, the changes in the treatment group sorting patterns are quite stark. In particular, the high school opening seem-

[29]These can have different denominations, the main ones being Greek Orthodox, Roman Catholic and Greek Catholic. In addition, some of these are exclusive to boys or girls.
[30]Typically, Hungarian or German, the two largest minority languages in Romania.

Table 3: DDD Regression Results

	Dependent variable:	
	Graduation Grade Percentile	
	(1 HS)	(2 HS)
Entrance Grade Percentile	0.690***	0.724***
	(0.011)	(0.016)
T	−0.025*	−0.182***
	(0.014)	(0.028)
T × q2	0.017	0.003
	(0.026)	(0.018)
T × q3	0.050**	0.092***
	(0.024)	(0.024)
T × q4	0.044***	0.103***
	(0.011)	(0.023)
Town FE	2+284	1+43
Year FE	11	11
Entrance Grade Quartile FE	3	3
Town × Quartile FE	286 × 3	44 × 3
Year × Quartile FE	11 × 3	11 × 3
Observations	157,835	79,770
Adjusted R^2	0.571	0.586
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows difference-in-difference-in-differences estimation results for school openings in towns with different numbers of high schools (Equation 6). Variable T is a dummy variable whose value is equal to one in towns where a new high school opens and after the opening, q is the entrance grade quartile of students (at the national cohort level).

ingly allows students with entrance scores in the 75^{th} percentile and above to cluster together at the school level. Students below the 75^{th} percentile are less likely to attend the same school as these top students as a result.

The triple difference results, which exploit disturbances in sorting patterns caused by school openings in few high-school towns, are presented in Table 3. First of all, the data suggest that a school opening in such a town reduces the graduation grade percentile of low entrance grade students. The graduation score gap between these students and above-median entrance score students widens after the school opening when compared to similar towns with no school openings.

Conditional on their entrance scores, the graduation gap between above-median entrance score students and their low entrance score counterparts widens by 4 to 10 percentiles in towns where a new high school opened compared to towns with no new openings.[31] Perhaps even more worryingly, there is evidence suggesting that conditional on entrance scores, school openings decrease graduation scores, on average.

These findings suggest that school construction benefits are not equally distributed among students of different abilities. While Duflo (2001) uses Indonesian data to suggest that school construction has strong and persistent effects on average educational outcomes and wages, the Romanian data suggest that, at least in a context in which there is school choice, high-ability students disproportionately absorb these gains. Meanwhile, low-ability students may actually be negatively impacted by school construction, as they become more segregated from their high-ability counterparts. Overall, the results indicate a possible decrease in average graduation scores in towns where new high schools open.

To summarize, both using differences in numbers of high schools across locations and high school openings confirm the causal link between increases in sorting and increases in achievement gaps between high- and low-entrance grade students. In the following sections, I explore the possible channels through which sorting plausibly affects student achievement.

4.1.3 Identification Concerns and Robustness Checks

Town Size A potential issue with identification is that the number of high schools correlates with other underlying, unobserved town-level characteristics that are the main drivers of increasing grade inequality.

For example, in towns with more high schools, socioeconomic inequality between high entrance score and low entrance score students may be higher. This inequality could then explain the increasing graduation gaps. Low entrance score students in large, many-high school towns may be poorer, face more social exclusion, on average, than their counterparts in small, few-high school towns, which may later have a bearing on their scores at graduation. Adding middle

[31] In the alternate specification, I estimate that the opening of a new school which accounts for 10% extra seats in that town will cause a 2 to 4 percentile widening of the gap between lowest-quartile students and their above-median counterparts post-opening in one and two high school towns, respectively. This is consistent with entrance grade sorting heterogeneously affecting student results post-opening. As before, higher levels of sorting are detrimental to low entrance score students and benefit high entrance score students.

school fixed effects partially addresses this concern. Middle schools in Romania are more numerous than high schools and typically serve a relatively narrow geographic area, especially in cities. Thus, middle school fixed effects can control for neighborhood-specific average characteristics.

Moreover, if student selection into towns driven by unobservable characteristics and socioeconomic differences unaddressed by middle school fixed effects are real concerns, controlling for the student populations in towns and interacting it with student abilities mitigates these issues. These interaction terms add extra flexibility to the model. They capture differences in the performance of students with similar entrance scores across towns of different populations. Once these controls are introduced, the instrument captures only differences in sorting patterns mechanically resulting from differences in high school numbers across locations, conditional on town populations.

Migration Another issue is migration. Given the institutional setup in Romania, where there are no school districts, there are no barriers preventing students from migrating to attend a specific high school. The concern is that more motivated or academically inclined students sort into larger, many-high school towns to attend better schools, which would bias results.

I propose two solutions to this problem. First of all, geographic migration is limited. Indeed, roughly 70% of all high school students attend a high school at most 10 km away from their middle school, while over 90% of them attend a high school at most 30 km away from the middle school they attended. In this sense, even if there is migration, the data suggest it is limited in scope and that the hometown of a student plays a big role in the type of school they attend.

Second, I estimate an alternate specification to the IV estimation. Instead of using towns as separate educational markets, I define these markets endogenously. For example, if a non-negligible number of students[32] graduating from a middle school attend high schools in town A, I consider this middle school to be part of the same educational market, even if it is not loacted in the same town. Moreover, if sufficiently many students from other middle schools enroll in high schools in both town A and B, then both towns A and B will be considered part of the

[32]In practice, I use different specifications to decide this threshold. However, these do not affect the estimated IV results significantly.

same market. I then reestimate the IV specification, replacing towns with these endogenous markets. I also estimate this new specification after excluding all students who migrate (i.e. who attend high school in a different market than their middle school; there are approximately 7% of these in my data). The second stage results are presented in Tables **??** to **??** of the Appendix. The results are very robust to these different specifications. Indeed, attending a high school (high school track) with a one percentile higher average entrance score causes an average score increase of 0.15 (0.30) percentiles when using the number of high schools across market rather than across towns as instruments. This estimate is 0.13 (0.27) percentiles when excluding across-market migration.

Sample Selection Lastly, there is a possible sample selection issue: I can only observe the graduation grades of students who write the graduation exam and not of those who drop out of high school. In order to address this, I use a Heckman two-stage correction for models with endogenous variables. 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 conditional on entrance grade, this instrument does not affect high school performance, but 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 D.

5 Decomposing Sorting Effects

In this section, I analyze three possible channels through which student sorting plausibly impacts grades. First, student sorting may directly impact scores via peer or social effects. Second, high entrance score students may sort into schools with higher ability teachers, which would likely improve their graduation scores. Third, high entrance score students may sort into schools with better classroom learning facilities or better infrastructure.

5.1 Sorting Patterns

5.1.1 Teacher Sorting

I now turn to teacher sorting. Teacher sorting patterns display two main trends. These are are summarized in Table 4. The first trend is that teachers sort on test scores both across towns and within towns. Second, high-scoring teachers disproportionately work in schools attended by high-admission score students.

To be more specific, higher test score teachers are more likely to work in larger towns, as shown in the first row of the table. While teachers in locations with one high school on average score in the 47th percentile on their placement exam, this figure is the 54th percentile in locations with 16 or more high schools. Teacher sorting by test scores across high schools is strong. Across towns with similar numbers of high schools (row 2), the palcement scores of coworkers teaching the same subject display a correlation of around 0.25, regardless of town size. Within towns (row 3), sorting is far more pronounced in localities with many high schools. These two findings together suggest that in smaller towns, there is significant across-town sorting of teachers on placement scores, but but less within-town sorting. For many-high school locations, teachers sort on placement scores across high schools, but not so much across towns.

Moreover, teacher sorting mirrors student sorting, with higher-scoring teachers disproportionately teaching high entrance-score students. Rows 4 suggests that high-scoring teachers are hired by schools attended by high-scoring students and this effect is more pronounced in locations with many high schools, where access to good teachers is particularly difficult for low-scoring students.

In summary, there is evidence of teacher sorting. High-scoring teachers tend to sort into the same schools and these schools are disproportionately urban, more selective schools. The two findings are important. To the extent that teacher placement scores correlate with teacher value-added, this raises concerns about inequalities due to school choice. Indeed, the implication is that high-scoring students will be able to sort into schools with high-scoring teachers and receive a better education, while low-scoring students will farther be penalized by being segregated into schools not only with lower-achieving peers, but with less competent teachers.

Table 4: Teacher Sorting

Number of High Schools in Town	1	2	3	4-15	16+
Average Teacher Score (Percentile)	47	47	49	49	54
Teacher-Coworker Score Correlation	0.25	0.23	0.32	0.27	0.29
Average within-Town Teacher-Coworker Score Correlation	−0.11	0.13	0.23	0.21	0.30
Teacher-Student Score Correlation	0.04	0.11	0.07	0.12	0.14

a

5.1.2 School Spending

Next, I investigate whether high entrance score students attend high schools that spend relatively more money per student. This may either be due to students preferring high schools which spend more per capita or, alternatively, schools who attract high entrance score students may be able to harness more financial resources for their students subsequently.

Either way, if student sorting is correlated to school expenditures, one should observe high entrance grade students disproportionately attending high budget schools. In order to study this, I estimate several versions of the following model, for student i attending high school h:

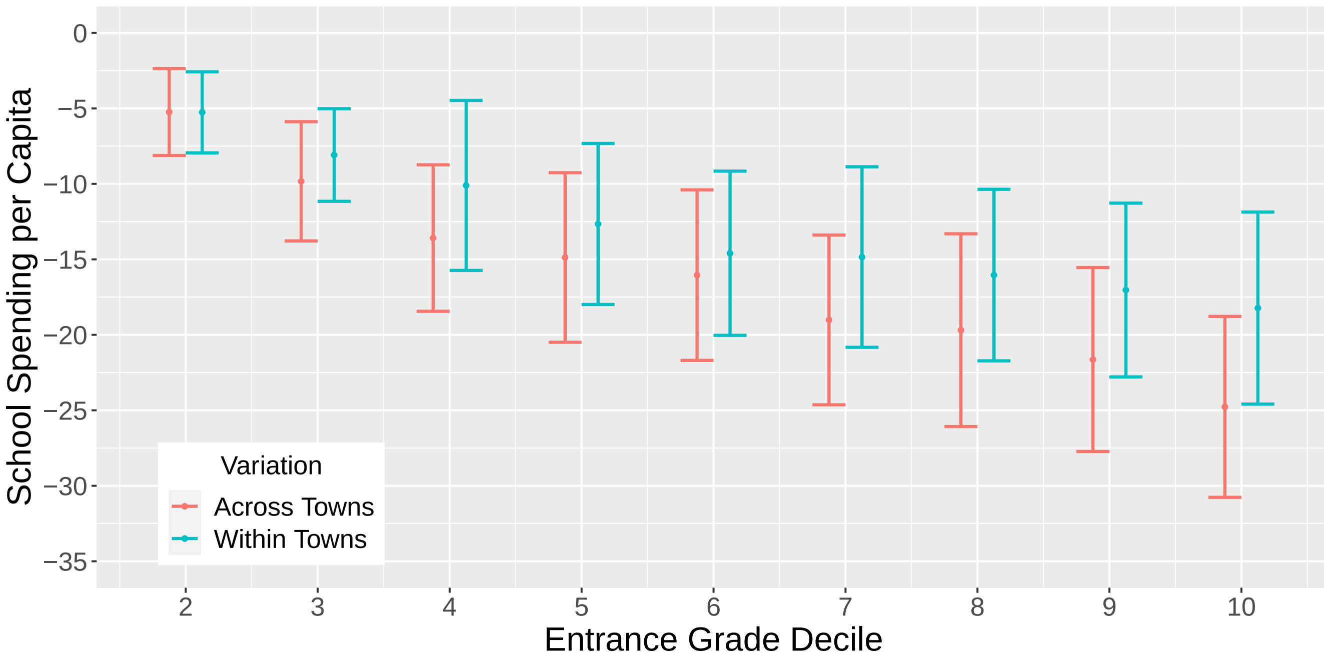
$$\exp_h = \beta_0 + \delta_d + \delta_n + \delta_l + \delta_y + \delta_{d\times n} + \epsilon_{i,h} \tag{7}$$

Here, $\exp_h$ is the average annual per-student expenditure of high school h. Fixed effects are denoted by δ. They include: δ_d (entrance grade decile), δ_n (number of high schools in town), δ_l (town), δ_y (year) and $\delta_{d\times n}$ (town size-entrance score decile).

The results are presented in Figure 10 and Table 18 in the Appendix. The results suggest several interesting patterns in the school expenditures. First, low-entrance score students receive more money per capita than their high-entrance score counterparts. Indeed, top decile students receive €25 per capita per year less than the bottom decile students.[33] This suggests that the government is making efforts to target spending towards disadvantaged students.

[33]The average amount is €30 per student per year and the standard deviation is roughly €60.

Figure 10: School Expenditure vs Entrance Grades



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

Second, these differences are only partially explained by differences in spending between towns. Indeed, the higher spending for low-achieving students is present within towns, as well as across towns.

Third, larger schools spend less money per student, possibly due to economies of scale. Indeed, a one standard deviation increase in entering cohort size is associated to a €10 per capita per year decrease in per capita school expenditure. However, even controlling for school size, lower-ability students, on average attend schools with higher per student spending, both within towns and across the entire country.

5.2 Effects on Grades

5.2.1 Peer Effects

Having shown a relationship between differences in sorting levels and variation in achievement gaps across the ability distribution, I now turn towards plausible channels through which sorting affects student performance. First, it is possible that sorting affects student grades via peer effects. Specifically, if sorting levels are high, high entrance score students are more likely to have high-ability schoolmates or classmates. Low entrance score students are more likely to have schoolmates or classmates that are of low-ability. To the extent that students generate learning spillovers that affect their peers', high levels of sorting can create virtuous feedback loops for high-ability students and negative feedback loops for low-ability students.

To estimate the peer effects, I use the year to year variation in the entrance grades of different cohorts within the same school. The idea is that, if school quality[34] is relatively stable over time, then the differences in average entrance score within a school from one year to another are quasi-random. Indeed, given the relatively small number of students admitted to a given high school in a given year, one would expect small, random deviations in entering cohort ability from year to year. This assumption can break down if unobserved school characteristics change over time and the student applicant pool also changes in response to this. However, anecdotally speaking, the rankings of high schools in Romania are quite persistent and the admission system enforces this persistence: a good school attracts top students and top teachers, which in turn creates a virtuous cycle, attracting more high-scoring students and teachers. In order to capture peer effects, the estimated equation is:

$$\begin{aligned} g_i =& \beta_0 + \beta_e e_i + \beta_\mu \mu^e_{-ihy} + \delta_l + \delta_h + \delta_m + \delta_p + \delta_y + \delta_s + \delta_d + \\ & \delta_n + \delta_{n\times d} + \delta_{h\times p} + \delta_{s\times d} + \epsilon_i \end{aligned} \tag{8}$$

Here, g_i is student i's high school graduation percentile, e_i is their high school entrance percentile, μ^e_{-ihy} is the peer mean entrance percentile in high school h and cohort y, excluding student i. Fixed effects are denoted by δ. I include the following fixed effects: town (δ_l), high school (δ_h), middle school (δ_m), high school track or program type (δ_p), year (δ_y), number of high school students admitted in town l and year y (δ_s), entrance decile within town-year (δ_d), number of high schools in town (δ_n) and interactions $\delta_{n\times d}$, $\delta_{h\times p}$ and $\delta_{s\times d}$.

While μ^e_{-ihy} is endogenous because it directly results from a student decision to enroll in high school h, conditioning on high school and track fixed effects ($\delta_{h\times p}$) means that β_μ will be identified by the yearly variation in the average entrance grade of students within high school tracks, which I assume to be quasi-random. If the quasi-randomness assumption is true, then

[34] In terms of facilities, teachers or any other factor that impacts student achievement except for peer effects.

conditional on high school, β_μ will be the coefficient of interest and will capture peer effects on the student graduation grades.

The estimation results for the peer effects regressions are presented in Table 5, where a student's peers are defined as students entering the same track, within the same high school, in the same year. The most relevant model is the full-fixed effects models and are presented in columns (5) of table 5. In this specification, I am comparing students enrolled in the same track within the same high schools, but who happen to have peers of different abilities. As a robustness check, similar models are estimated at the high school, rather than high school-track level.[35] Once all fixed effects are included, the results suggest the absence of a meaningful relationship between variations in peer ability and student graduation scores.

Lastly, in order to allow for possible heterogeneity in the peer effects, I estimate and alternative specification in which I interact the student's relative ranking within their school's entering cohort with the peer average entrance score:[36]

$$\begin{aligned} g_i =& \beta_0 + \beta_e e_i + \beta_\mu \mu^e_{-ihy} + \delta_l + \beta_{\mu,d}(\mu^e_{-ihpy} \times d_{hpy}(e_i)) + \delta_h + \delta_m + \delta_p + \delta_y + \delta_s + \delta_d + \\ & \delta_n + \delta_{n\times d} + \delta_{h\times p} + \delta_{s\times d} + \epsilon_i \end{aligned} \tag{9}$$

The estimated results are shown in Table 20 in the Appendix and illustrated in Figure 11. The peer effects increase with a student's rank within their entrance grade track (or school). Only high entrance score students benefit from increases in cohort ability, while lower entrance score students are negatively affected by having stronger peers. This is consistent with survey results by Pop-Eleches and Urquiola (2013), who show that students near the entrance score thresholds in Romania are more likely to face bullying, social exclusion and low confidence of their ability than students with similar grades who attend less selective schools. This type of heterogeneity in peer effects is consistent with the single crossing peer effects models, as per Sacerdote (2011).

[35] Results are presented in Table 19 of the Appendix.

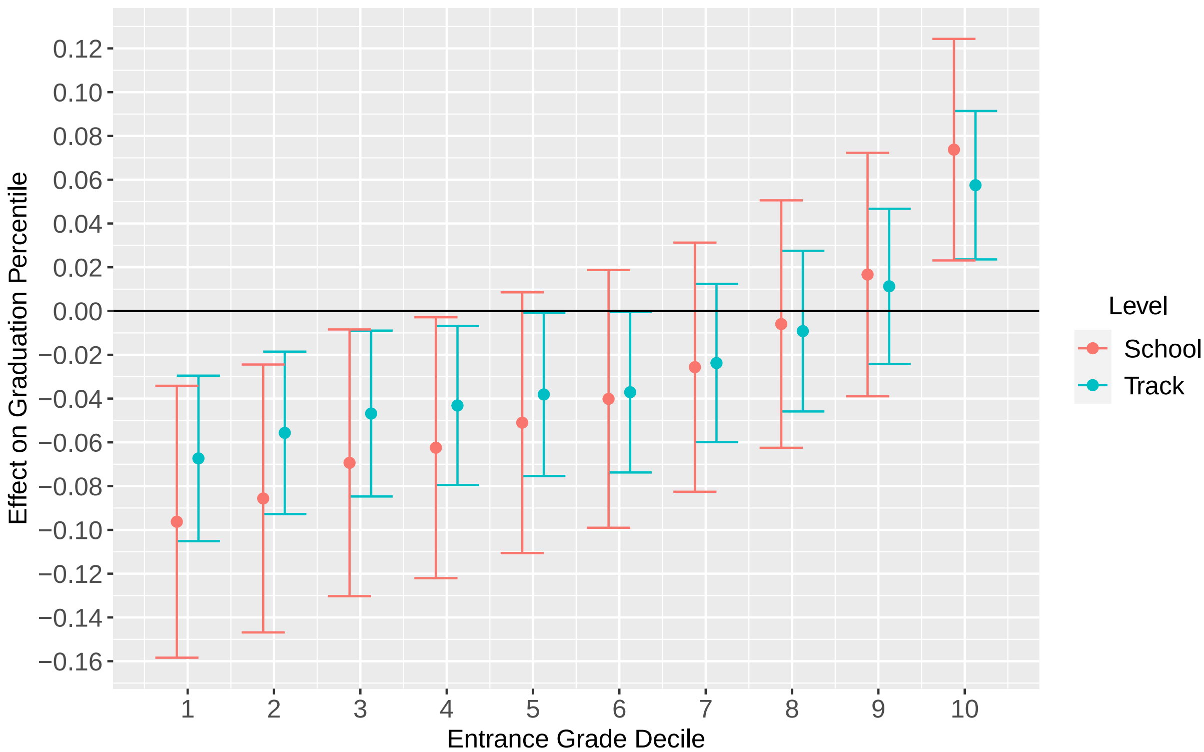
[36] Where g_i is student i's high school graduation percentile, e_i is their high school entrance percentile, μ^e_{-ihy} is the peer mean entrance percentile in high school h and cohort y, excluding student i and the following fixed effects are included: town (δ_l), high school (δ_h), middle school (δ_m), high school track or program type (δ_p), year (δ_y), number of high school students admitted in town l and year y ($\delta_{s_{ly}}$, abbreviated δ_s), entrance decile within town-year ($\delta_{d_{ly}}$, abbreviated δ_d), number of high schools in town ($\delta_{n_{ly}}$, abbreviated δ_n) and interactions $\delta_{n\times d}$, $\delta_{h\times p}$ and $\delta_{s\times d}$. Lastly, I include an interaction term $\mu^e_{-ihpy} \times d_{hpy}(e_i)$ (interaction between student ability and peer ability at high school entrance) that will capture heterogeneities in peer effects.

Table 5: Peer Effects Regression (Track Level)

	Dependent variable:					
	Graduation Exam Percentile					
	(1)	(2)	(3)	(4)	(5)	(No HS,HS-Track FE)
Entrance Grade Percentile	0.532***	0.536***	0.515***	0.515***	0.531***	0.531***
	(0.032)	(0.032)	(0.021)	(0.021)	(0.019)	(0.019)
Mean Entrance Percentile (HS-Track-Cohort)	−0.063***	−0.066***	−0.009	−0.009	−0.017	−0.017
	(0.023)	(0.023)	(0.019)	(0.019)	(0.017)	(0.017)
Number of High School Students (Town-Yr)	Yes	Yes	Yes	Yes	Yes	Yes
Entrance Decile (Town-Yr) FE (1+9)	Yes	Yes	Yes	Yes	Yes	Yes
Number of HS in Town FE (1+5)	Yes	Yes	Yes	Yes	Yes	Yes
Number of HS in Town × Entrance Decile	Yes	Yes	Yes	Yes	Yes	Yes
Number of HS Students (Town-Yr) × Entrance Decile	Yes	Yes	Yes	Yes	Yes	Yes
HS FE (1+1,470)	Yes	Yes	Yes	Yes	Yes	No
HS-Track FE (8,984)	Yes	Yes	Yes	Yes	Yes	Yes
Town FE (1+557)	No	Yes	Yes	Yes	Yes	Yes
Year FE (1+11)	No	No	Yes	Yes	Yes	Yes
Track FE (1+557)	No	No	No	Yes	Yes	Yes
MS FE (1+19,214)	No	No	No	No	Yes	Yes
Observations	1,182,897	1,182,897	1,182,897	1,182,897	1,182,897	1,182,897
Adjusted R^2	0.619	0.619	0.639	0.639	0.665	0.665

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the town level.
This table shows the relationship between graduation exam scores and average entrance score of students within high school-track-year, conditional on own entrance grade. By controlling for high school-track fixed effects, I identify effects on graduation grades caused by year-to-year variation in track-level cohort peer ability.

Figure 11: Heterogeneity in Peer Effects



Note: This figure plots the marginal effect of an increase in average high school peer entrance score on own high school graduation exam percentile (i.e. $\beta_{\mu,d}(\mu^{e}_{-ihpy} \times d_{hpy}(e_i))$ in equation 9).

5.2.2 Teacher Ability

I now turn towards the effects of teacher ability on high school performance. I use the following specification, which includes an interaction term between student entrance grade decile and teacher ability, in order to capture any complementarities between student and teacher skill:[37]

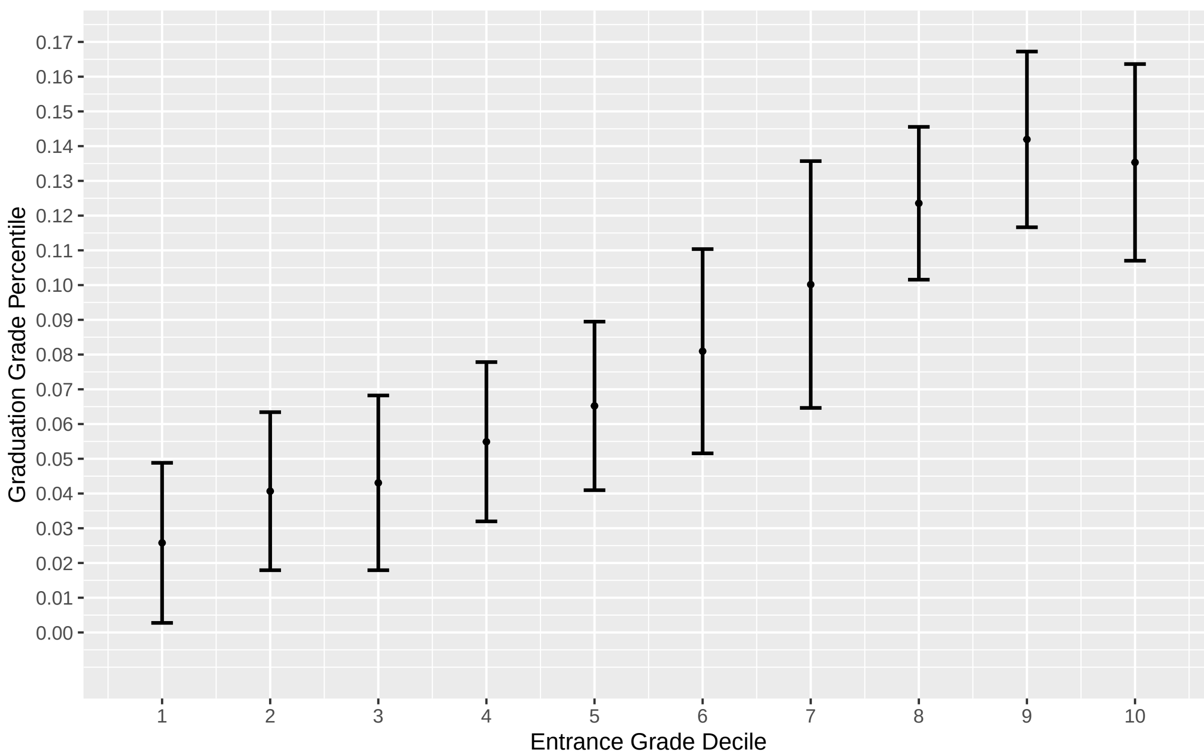
$$g_{ic} = \beta_0 + \beta_e e_i + \beta_t t_{hyc} + \beta_{d\times t} d \times t + \delta_d + \delta_n + \delta_l + \delta_y + \epsilon_{i,j} \tag{10}$$

Results are presented in Table 21 in the Appendix and illustrated in Figure 12. Conditional

[37]This regression is at the student-subject level. Variable g_{ic} is the student percentile on the high school graduation exam component c (the graduation exam has a Romanian language component, a mandatory field-specific component and an elective component), e_i is the student percentile on the high school entrance exam, t_{hyc} is the average entrance grade of teachers teaching subject component c in high school h who could have taught graduating class y, weighted by the number of hours they teach per week. For example, for graduating class 2019, I include all teachers working in the high school between the years 2015 and 2019. I also include fixed effects for: number of high schools in town (n_{ly}, abbreviated to n), town (l), entrance grade decile ($d_y(e_i)$, abbreviated to d_y) and year (y). Lastly, I add an interaction term $d \times t$ such that $\beta_{d\times t}$ captures complementarities in teacher-student ability.

on entrance scores, students who attend schools with higher ability teachers in a particular subject tend to score higher on that subject during the high school graduation exam. A one percentile increase in high school teacher score percentile is associated with a 0.08 increase in graduation exam percentile. Note that, in the data, it is impossible to observe exactly which teacher teaches which students. Therefore, this point estimate likely represents a lower bound for the effect of teacher ability on graduation grades. For example, a high-ability teacher who only teaches one class will realistically have no direct effect on students' graduation grades in other classes, but still boosts average teacher ability within the high school in the data.

Figure 12: Heterogeneity in Teacher Effects on Graduation Grades



Note: This figure plots the marginal effect of a one percentile point increase in average teacher examination score own high school graduation exam percentile (for a given subject), by student entrance score decile, with 95% confidence intervals.

The last four columns of the table show that the teacher ability effect estimate hides significant heterogeneities in teacher effects across student ability. By interacting student entrance score ranks within high schools or high school tracks, I find that high entrance score students benefit more from high-ability teachers than low entrance score students. In fact, estimates suggest that top decile students benefit from a one percentile point increase in teacher ability is roughly four times that of bottom decile students. This result applies both when comparing students in different high schools and tracks and within tracks of the same high school. This result is thus not driven by teachers selecting into tracks with higher ability students within high schools. This result, along with high-ability teachers sorting into schools where high-ability students enroll, may partially explain the widening gap in high school achievement during high school.

Although the mechanism through which this occurs remains an open question, relatively high-ability students may receive more teacher attention. It could also be that teachers teach more challenging or a higher volume of material when higher entrance score students are present and that lower-ranked students have difficulties keeping up. It is also possible that students who rank relatively low in a classroom suffer from self-confidence issues that hamper their ability to take advantage of high-ability teachers.

Lastly, the heterogeneity observed in teacher effects is policy-relevant as it potentially limits the scope for narrowing the student achievement gap by moving high-ability teachers to teach low-entrance score students. Moving high-ability teachers to worse schools may help alleviate inequalities in outcomes at graduation. However, relatively higher entrance score students within these schools are likely to benefit more from such a policy.

5.2.3 School Expenditures

An additional channel through which sorting can affect student performance on the high school exit exam is school resources and infrastructure. For example, good quality science and computer labs or interactive classroom equipment can improve student grades. Conversely, poor classroom conditions, such as inadequate heating in winter or low-quality meals could adversely impact student attendance rates, concentration and performance. Suppose students prefer attending high schools endowed with good infrastructure. In that case, given the nature of the admissions system, high entrance score students will disproportionately be admitted to good infrastructure schools. This would exacerbate the performance gap between high- and low-ability students.

Table 6: 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.

Even though the data suggest that there is no systematic sorting of students along ability into schools with different spending patterns (Table 18), it could still be the case that school spending influences student performance. To that end, I estimate the following specification, regressing graduation scores on average per student yearly high school expenditures:

$$g_i = \beta_0 + \beta_e e_i + \beta_{\exp} \exp_h + \beta_{\exp \times n} \exp \times n + \delta_n + \delta_l + \delta_y + \epsilon_i \tag{11}$$

Here, g_i is the student percentile on the high school graduation exam, e_i is the student percentile on the high school entrance exam, $\exp_h$ is high school h's average yearly per graduating student expenditure (in hundreds of Euro) and including fixed effects for: number of high schools in town (n), town (l) and year (y).

Table 6 outlines that the student performance gap at graduation is little if at all impacted by differences in school spending. The data suggest a small and negative correlation between school spending and graduation grades. This likely means that, with high entrance score students sorting into schools with lower per-student expenditures than low entrance score students, graduation scores are affected by some other factor, for example, teacher ability, which is negatively correlated with school expenditures.

Note that school expenditures here exclude staff wages and represent a flow variable that may be uninformative of the infrastructure stock accumulated in a school. In that sense, if schools with an infrastructure deficit are more likely to spend more money in order to close this gap, the results in Table 6 can be consistent with infrastructure having a positive effect on grades and driving some of the observed graduation grade gap. Unfortunately, data on material school stock is not available.

5.3 Decomposing Sorting Effects

I explored the relationship between peer effects, school spending, teacher ability and graduation grades. The evidence suggests that teacher and peer abilities are associated with better educational outcomes and may widen performance gaps. On the other hand, peer effects and school expenditures seem to have a much smaller, if any, impact on school performance. I now provide a simple model explaining each of these three channels' relative importance in explaining the effect of student sorting on performance. I use the following baseline model:

$$g_i = \beta_0 + \beta_e e_i + \beta_\mu \hat{\mu}^e_{\text{-ih}} + \delta_n + \delta_d + \delta_y + \delta_l + \epsilon_i \tag{12}$$

Here, g_i is the student percentile on the high school graduation exam, e_i is the student percentile on the high school entrance exam and μ^e_{-ih} is the mean entrance exam grade in high school h, excluding student i.[38] Fixed effects are denoted by δ and include the following: δ_d (town-cohort entrance grade decile of student i), δ_n (number of high schools in town), δ_y (year) and town (δ_l).

I instrument $\hat{\mu}^e_{\text{h}}$, using the relative rank of a student within their town ($d_{ly}(e_i)$), interacted with the number of high schools in that town (n_{ly}):

$$\mu_{hy} = \gamma_0 + \gamma_e e_i + \eta_n + \eta_d + \eta_{d\times n} + \eta_y + \eta_l + \xi_i \tag{13}$$

This baseline specification is then sequentially augmented to include measures of high school-

[38] Note that this is slightly different than the specification in Equation 3. In that model, I used high school-year entrance grade averages (μ^e_{-ihy}) as a proxy of school quality. Here, I am using high school entrance grade averages. The reason is that I want to use yearly changes in cohort ability to identify peer effects, while the time-invariant average is used to proxy school quality over the entire sample period.

level teacher ability (μ^t_{hy}), school expenditures per student ($\exp_h$) and peer ability (more specifically, the yearly deviation from the mean in peer entrance scores, $\mu_{hy}(e_i) - \mu_h(e_i)$):

$$\begin{aligned} g_i = &\beta_0 + \beta_e e_i + \beta_\mu \hat{\mu^e_{\mathrm{h}}} + \delta_n + \delta_{d_l(e_i)} + \delta_y + \delta_l + \\ &\beta_t \mu^t_{hy} + \beta_{\exp}\exp_h + \beta_{\mathrm{peer}}(\mu_{hy}(e_i) - \mu_h(e_i)) + \epsilon_i \end{aligned} \tag{14}$$

After adding teacher, expenditure and peer variables, we can observe how the coefficient of interest β_μ changes. If this coefficient shrinks to the point of becoming insignificant, it is possible to conclude that the three channels we consider explain most of the sorting effects on graduation grades. Moreover, by adding the variables to the model one by one and observing the impact on β_μ, I can quantify the relative impact of each channel in explaining the effects of sorting.

Table 7: Decomposition of Sorting Effects (Second Stage)

	Dependent variable:					
	Graduation Exam Component Percentile					
	(Baseline)	(Peers)	(Teachers)	(Exp)	(P+T)	(P+T+E)
Adm. Score Percentile (Ro)	0.155***	0.145***	0.158***	0.155***	0.147***	0.147***
Adm. Score Percentile (Math)	0.070***	0.059***	0.076***	0.070***	0.070***	0.063***
Peers (School)		−0.178***			−0.178***	−0.185***
Teacher			0.097***		0.097***	0.096***
Expenditure				−0.001		−0.002*
Instrumented Peer Adm. Score (School)	0.063*	0.048	0.028	0.060*	0.013	0.009
Number of High Schools in Town	4	4	4	4	4	4
Town-Cohort Adm. Score Decile (d)	10	10	10	10	10	10
N. Students Cohort (Town-Year)	Yes	Yes	Yes	Yes	Yes	Yes
N. Students Cohort (T-Y) × d	Yes	Yes	Yes	Yes	Yes	Yes
Town Unemployment Level	Yes	Yes	Yes	Yes	Yes	Yes
County HS Dropout Rate	Yes	Yes	Yes	Yes	Yes	Yes
County Average Wage	Yes	Yes	Yes	Yes	Yes	Yes
Town FE	337	337	337	337	337	337
Year FE	5	5	5	5	5	5

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the town level.
This table shows estimation results of Equation 14. It shows the relationship between graduation exam subject scores (e.g. math, Romanian) and school quality, proxied by average admission scores, conditional on own entrance grade. Each column represents a specification in which I add peer effects, teacher ability and/or school expenditure to the baseline model. Number of high schools are grouped into four bins. Town-cohort admissions core deciles (d) are student entrance exam deciles within their town and cohort; reference level is the bottom entrance grade decile (d1). Peer quality is identified by the differences in within-school average admission scores from year to year. Teacher ability is the average placement test percentile of teacher who worked during a student's four year stay, weighted by the number of weekly hours worked. Since I look at graduation exam components separately, onlyteachers teaching relevant subjects are included on the righ-hand side (e.g. math and physics teachers for science component grades). Expenditures are measured in hundreds of Euro/student/year. Peer admission scores are instrumented by an interaction of town-cohort admission deciles and the number of high schools within a town.

Table 7 presents the results of this decomposition. The baseline specification shows that going to a school with a one percentage point higher average entrance grade causes a 0.069 percentile increase in graduation grade.[39] A similar specification at the track-level is estimated in Table 22.

I find that the three channels explored in this paper explain 78% (83%) of the effects of attending a better high school (track). Using a Gelbach decomposition,[40] I find that at the high school level, differences in teacher ability, peer effects and school spending account for 62%, 32% and 6%, respectively of the explained component. As much as 84% of the explained variation is accounted for by differences in teacher ability at the track level. These two findings imply that, within high schools, there are significant track-level differences in teacher ability. Meanwhile, peer effects and school expenditures only account for 7% and 9% of track-level explained variation.

It is plausible that the estimates for teacher ability's relative contribution are relatively conservative for two reasons. First of all, the teacher data is quite noisy and only captures new hires, of which many are temporary teachers. There is no information on the variation of the abilities of existing teachers within a school. Second, and perhaps more importantly, the data does not allow the matching of students to teachers. As such, the variation in teacher ability is at the school-year level. I expect the hiring of a new teacher to have a relatively small impact on the average student's graduation grade in a school. Indeed, this teacher will only be matched to some classes of the four grades in a high school.

Thus, the decomposition shows that student sorting affects performance mainly by creating inequalities in access to competent teachers. While peer effects and school expenditures do seem to play a role, their contribution is dwarfed by that of teachers.

[39] This is different from the IV specification results for several reasons. First of all, the sample used here is restricted to the students who have matching teachers and school expenditures. Moreover, the school quality proxy used in the present specification is the mean entrance score of student within the school, rather than the mean in the year a student was admitted. This is because I want to use the yearly variation in cohort ability to identify peer effects. Lastly, graduation and entrance scores are broken down by subject component to match the data to the teacher data, which is subject-specific.

[40] Intuitively, this decomposition is not sensitive to the order in which we add the explanatory variables to the full model and capturing variance and covariance structures of the variables of interest. For more details, consult Gelbach (2016).

6 Discussion and Conclusion

This paper investigates the effects of student sorting along ability on educational outcomes. The competitive high school admission system in Romania gives rise to very extreme sorting patterns that display significant and systematic geographic variation that can be used to identify the effects of sorting on student outcomes. Moreover, student admission and graduation records are matched to teacher ability and school expenditure data for the first time, which allows the exploration of the different channels through which sorting impacts school performance.

I first document how students sort in schools and how this sorting affects student grades. I find that sorting markedly increases in the number of high school choices available to students. As the number of local high schools increases, segregation of students across ability rises markedly and there is a widening the performance gap between high-ability and low-ability students. Thus, the data paint a stark picture when it comes to school choice policies: increases in school choices exacerbate educational inequalities.

Second, I decompose the channels through which sorting impacts school outcomes. While peer effects are not, on average, significant, there is significant heterogeneity: high entrance score students within tracks or schools benefit from having better peers, while this is detrimental to low entrance score students.

I also show that teacher sorting closely mirrors student sorting, such that high-ability students are more likely to attend schools where high-ability teachers work. This happens in two ways: high-ability teachers are more likely to work in bigger cities and, within cities, high-ability teachers are more likely to find teaching positions in schools attended by high-ability students. This occurs despite the fact that teacher salaries do not vary by school or town in this educational system. By exploiting between-school variation in the quality of teaching bodies, conditional on student abilities, I find that high-ability teachers add value. Moreover, I find evidence that high-ability students benefit from high-ability teachers more than low-ability students.

To conclude, the results suggest that the main channel through which sorting increases inequality is access to high-ability teachers. A higher degree of school choice leads to a high entrance score students gaining access to higher ability teachers than their low entrance score counterparts. Moreover, peer and teacher ability results suggest that there are tradeoffs in terms of policy. Policymakers may reduce inequalities in education by either reducing the extent of student sorting[41] or by assigning high-ability teachers to low-ability students. However, doing this comes with an efficiency loss. There are performance complementarities to be obtained both by grouping high-ability students and assigning high-ability teachers to high-ability students.

Lastly, there is also a policy implication about school construction. While Duflo (2001) suggests that school openings have strong and persistent effects on average educational outcomes and wages, the Romanian data suggest that, at least in a context in which there is school choice, high-ability students are the main beneficiaries. Meanwhile, low-ability students may actually be negatively impacted by school construction. Overall, there is evidence that a new school opening in a location negatively affects average student scores while also increasing inequality.

[41] For example, by randomly assigning students to schools.

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Appendices

A Tables, Figures and Regression Results

Table 8: Regression of Graduation Grade vs Entrance Grade, by Town Size

	Dependent variable:					
	Graduation Grade Percentile					
	(1)	(2)	(3)	(4)	(5)	(6)
Entrance Grade Percentile	0.710***	0.582***	0.631***	0.571***	0.563***	0.644***
d2 × n2-6	−0.015**	−0.013*	−0.010	−0.014**	−0.014**	−0.015**
d3 × n2-6	−0.014*	−0.009	−0.005	−0.015**	−0.016**	−0.020***
d4 × n2-6	−0.011	−0.002	0.004	−0.015*	−0.016**	−0.022***
d5 × n2-6	0.0001	0.011	0.018**	−0.011	−0.010	−0.018**
d6 × n2-6	0.018*	0.031**	0.037***	0.001	0.003	−0.006
d7 × n2-6	0.029***	0.043***	0.048***	0.008	0.009	−0.001
d8 × n2-6	0.030***	0.044***	0.049***	0.012	0.013	0.002
d9 × n2-6	0.042***	0.055***	0.059***	0.025**	0.024**	0.014
d10 × n2-6	0.054***	0.060***	0.064***	0.036***	0.030***	0.023**
d2 × n7-15	−0.026***	−0.023**	−0.017*	−0.019**	−0.021**	−0.023***
d3 × n7-15	−0.031**	−0.022	−0.015	−0.018	−0.019*	−0.025**
d4 × n7-15	−0.016	−0.003	0.005	−0.007	−0.008	−0.018
d5 × n7-15	0.009	0.026	0.032**	0.008	0.008	−0.004
d6 × n7-15	0.040***	0.058***	0.063***	0.030*	0.028**	0.015
d7 × n7-15	0.059***	0.079***	0.081***	0.040***	0.038***	0.023*
d8 × n7-15	0.066***	0.087***	0.088***	0.047***	0.044***	0.028**
d9 × n7-15	0.075***	0.094***	0.094***	0.055***	0.049***	0.034**
d10 × n7-15	0.082***	0.092***	0.094***	0.058***	0.048***	0.038***
d2 × n16+	−0.014*	−0.006	0.0004	−0.0004	−0.002	−0.004
d3 × n16+	−0.008	0.007	0.015	0.013	0.009	0.002
d4 × n16+	0.003	0.023	0.032***	0.026**	0.021**	0.009
d5 × n16+	0.031**	0.055***	0.063***	0.043***	0.039***	0.025**
d6 × n16+	0.056***	0.082***	0.088***	0.055***	0.051***	0.035***
d7 × n16+	0.070***	0.098***	0.101***	0.063***	0.058***	0.041***
d8 × n16+	0.074***	0.102***	0.105***	0.068***	0.062***	0.044***
d9 × n16+	0.087***	0.112***	0.114***	0.080***	0.071***	0.055***
d10 × n16+	0.096***	0.110***	0.115***	0.084***	0.072***	0.061***
Entrance Grade Decile (1+9)	Yes	Yes	Yes	Yes	Yes	Yes
N HS Students (Town)	Yes	Yes	Yes	Yes	Yes	Yes
N HS Students (Town) × Entrance Grade Decile	Yes	Yes	Yes	Yes	Yes	Yes
N HS Town (1+4)	Yes	Yes	Yes	Yes	Yes	Yes
Town FE (1+537)	No	Yes	Yes	Yes	Yes	No
Year FE (1+11)	No	No	Yes	Yes	Yes	Yes
Track FE (1+116)	No	No	No	Yes	Yes	Yes
MS FE (1+19,271)	No	No	No	No	Yes	Yes
Observations	1,170,680	1,170,680	1,170,680	1,170,680	1,170,680	1,170,680
Adjusted R^2	0.518	0.539	0.568	0.599	0.635	0.633

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows the estimation results of Equation 2, where d is the entrance grade decile (at the town-cohort level) and n is the number of high schools in a town.

Table 9: Student vs High School Peers Entrance Grades

	Student Entrance Grade Percentile
d2	0.013***
d3	0.023***
d4	0.031***
d5	0.037***
d6	0.042***
d7	0.046***
d8	0.050***
d9	0.054***
d10	0.060***
Small Towns	−0.236***
Medium Towns	−0.257***
Large Towns	−0.273***
d2 × Small Towns	0.024***
d3 × Small Towns	0.059***
d4 × Small Towns	0.106***
d5 × Small Towns	0.167***
d6 × Small Towns	0.235***
d7 × Small Towns	0.303***
d8 × Small Towns	0.356***
d9 × Small Towns	0.392***
d10 × Small Towns	0.419***
d2 × Medium Towns	0.014***
d3 × Medium Towns	0.039***
d4 × Medium Towns	0.077***
d5 × Medium Towns	0.141***
d6 × Medium Towns	0.226***
d7 × Medium Towns	0.325***
d8 × Medium Towns	0.422***
d9 × Medium Towns	0.489***
d10 × Medium Towns	0.530***
d2 × Large Towns	0.008***
d3 × Large Towns	0.036***
d4 × Large Towns	0.086***
d5 × Large Towns	0.153***
d6 × Large Towns	0.248***
d7 × Large Towns	0.351***
d8 × Large Towns	0.443***
d9 × Large Towns	0.528***
d10 × Large Towns	0.600***
Town FE (1+554)	Yes
Year FE (1+11)	Yes
Observations	1,843,891
Adjusted R^2	0.766

Note: *p<0.1; **p<0.05; ***p<0.01.
This table shows the relationship between a student's entrance grade and their high school peer's average entrance grade.
Small Towns have 2-6 HS, Medium Towns have 7-15 HS, Large towns have 16+ HS; reference level is towns with one high school. Deciles (d) are student entrance grade deciles within their cohort (nationallu); reference level is the bottom entrance grade decile (d1).

Table 10: IV First Stage (School)

	Dependent variable:		
	Average Peer Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.662***	0.285***	0.269***
d2 × n2	−0.001	−0.002	−0.001
d3 × n2	0.011	0.009	0.010
d4 × n2	0.032**	0.029***	0.031***
d5 × n2	0.063***	0.053***	0.055***
d6 × n2	0.099***	0.086***	0.089***
d7 × n2	0.126***	0.110***	0.112***
d8 × n2	0.139***	0.123***	0.125***
d9 × n2	0.146***	0.132***	0.134***
d10 × n2	0.163***	0.143***	0.144***
d2 × n3	0.001	0.008	0.010
d3 × n3	0.008	0.014	0.019*
d4 × n3	0.023	0.028*	0.037***
d5 × n3	0.053**	0.052***	0.065***
d6 × n3	0.105***	0.097***	0.113***
d7 × n3	0.157***	0.141***	0.154***
d8 × n3	0.199***	0.179***	0.187***
d9 × n3	0.224***	0.203***	0.208***
d10 × n3	0.261***	0.226***	0.226***
d2 × n4-15	0.001	0.010**	0.012**
d3 × n4-15	0.019*	0.033***	0.040***
d4 × n4-15	0.050***	0.064***	0.075***
d5 × n4-15	0.102***	0.111***	0.124***
d6 × n4-15	0.163***	0.169***	0.184***
d7 × n4-15	0.237***	0.235***	0.247***
d8 × n4-15	0.301***	0.290***	0.297***
d9 × n4-15	0.352***	0.335***	0.337***
d10 × n4-15	0.411***	0.370***	0.367***
d2 × n16+	−0.006	0.010**	0.011
d3 × n16+	0.017	0.040***	0.045***
d4 × n16+	0.056***	0.080***	0.089***
d5 × n16+	0.117***	0.138***	0.141***
d6 × n16+	0.196***	0.211***	0.208***
d7 × n16+	0.274***	0.287***	0.273***
d8 × n16+	0.348***	0.353***	0.333***
d9 × n16+	0.424***	0.416***	0.390***
d10 × n16+	0.520***	0.481***	0.437***
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
Track FE	No	191	191
MS FE	No	18,921	18,590
Observations	1,180,088	1,180,088	1,161,360
Adjusted R^2	0.717	0.823	0.827
Weak Instrument Test p-value	0	0	0
Wu-Hausman p-value	0	0.54	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 3. 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.

Table 11: IV First Stage (Track)

	Dependent variable:		
	Average Peer Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.698***	0.370***	0.358***
d2 × n2	0.008	0.006	0.007
d3 × n2	0.014*	0.010*	0.011*
d4 × n2	0.022**	0.017**	0.018**
d5 × n2	0.034***	0.022***	0.023***
d6 × n2	0.046***	0.032***	0.033***
d7 × n2	0.051***	0.037***	0.039***
d8 × n2	0.053***	0.042***	0.044***
d9 × n2	0.062***	0.051***	0.053***
d10 × n2	0.083***	0.062***	0.064***
d2 × n3	0.001	0.005	0.006
d3 × n3	0.007	0.008	0.012
d4 × n3	0.013	0.012	0.019
d5 × n3	0.021	0.014	0.021*
d6 × n3	0.042**	0.029**	0.037***
d7 × n3	0.061***	0.046***	0.053***
d8 × n3	0.078***	0.062***	0.065***
d9 × n3	0.093***	0.077***	0.077***
d10 × n3	0.126***	0.095***	0.093***
d2 × n4-15	0.004	0.008*	0.009*
d3 × n4-15	0.011	0.019***	0.025***
d4 × n4-15	0.023*	0.029***	0.038***
d5 × n4-15	0.046***	0.046***	0.055***
d6 × n4-15	0.067***	0.067***	0.077***
d7 × n4-15	0.097***	0.093***	0.101***
d8 × n4-15	0.124***	0.118***	0.122***
d9 × n4-15	0.154***	0.145***	0.144***
d10 × n4-15	0.206***	0.175***	0.169***
d2 × n16+	0.000	0.007	0.010
d3 × n16+	0.012	0.022***	0.033***
d4 × n16+	0.029*	0.038***	0.054***
d5 × n16+	0.054***	0.058***	0.070***
d6 × n16+	0.089***	0.086***	0.091***
d7 × n16+	0.122***	0.122***	0.119***
d8 × n16+	0.158***	0.158***	0.149***
d9 × n16+	0.204***	0.198***	0.184***
d10 × n16+	0.284***	0.248***	0.217***
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
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	0.753	0.860	0.860
Weak Instrument Test p-value	0	0	0
Wu-Hausman p-value	0	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 3. 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.

Table 12: IV Second Stage (School)

	Dependent variable:		
	Graduation Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.590***	0.566***	0.530***
Instrumented Peer Admission Score (Percentile)	0.367***	0.322***	0.356***
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
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	0.638	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 3. 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.

Table 13: IV Second Stage (Track)

	Dependent variable:		
	Graduation Exam Score Percentile		
	(1)	(2)	(3)
Admission Score (Percentile)	0.486***	0.521***	0.454***
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
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	0.533	0.638	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 3. 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.

Table 14: DDD Regression Results (Continuous Treatment Variable)

	Dependent variable:	
	Graduation Exam Percentile	
	(1 HS)	(2 HS)
Entrance Grade Percentile	0.690***	0.723***
	(0.011)	(0.016)
Trt Intensity	−0.081	−1.370***
	(0.090)	(0.205)
Trt Intensity × q2	0.054	−0.220
	(0.083)	(0.142)
Trt Intensity × q3	0.165***	0.357*
	(0.059)	(0.192)
Trt Intensity × q4	0.152**	0.442**
	(0.066)	(0.185)
Town FE	3+284	2+43
Year FE	11	11
Entrance Grade Quartile FE	3	3
Town × Quartile FE	287 × 3	45 × 3
Year × Quartile FE	11 × 3	11 × 3
Observations	157,835	79,770
Adjusted R^2	0.574	0.588

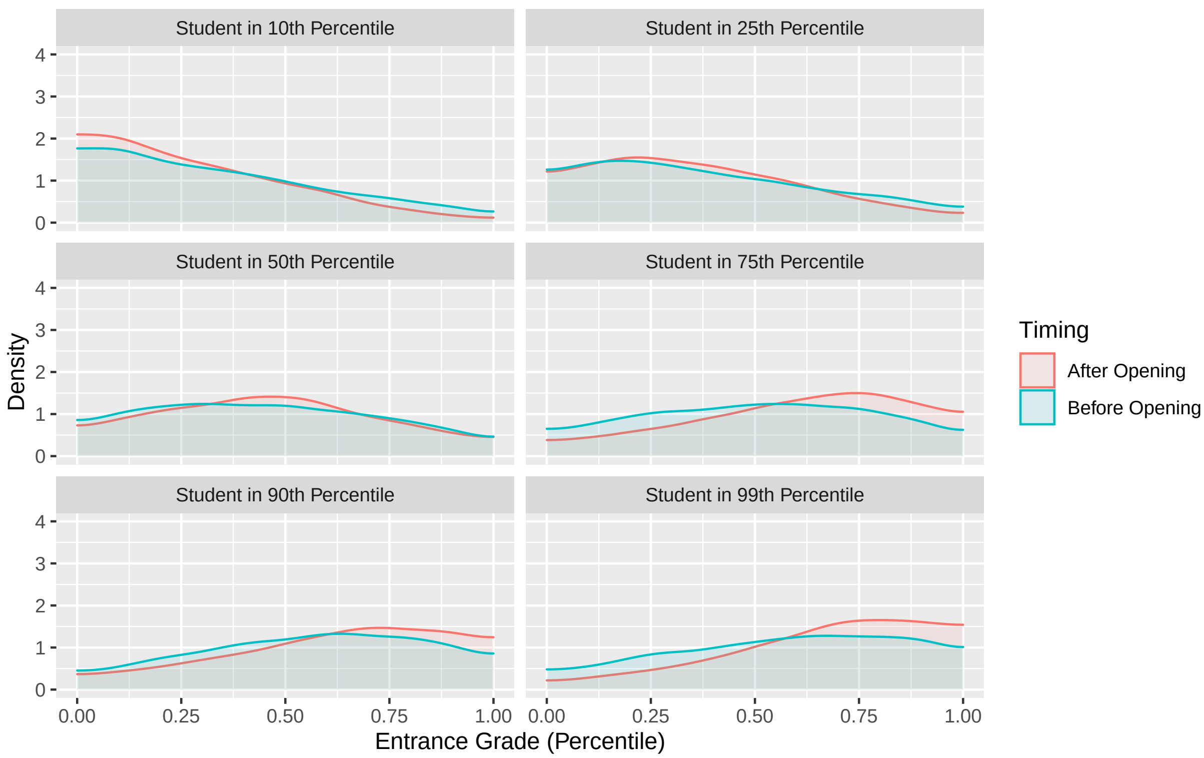
Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows difference-in-difference-in-differences estimation results for school openings in different town sizes, i.e. 6. Variable Trt Intensity is the number of seats in a newly opened school as a proportion of the number of seats in old schools in a town, q is the entrance grade quartile of students (at the town-cohort level).

Table 15: List of HS Openings

Number of HS (before opening)	Occurences	First Full Cohort Graduation Year
1	2	2012, 2017
2	1	2011

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.

Figure 13: DDD: Sorting Patterns Before and After School Opening (Control Group), by Entrance Score



Note: This figure plots the distribution of student peers (within the same school) in the control group, conditional on own entrance score, before and after high schools open in the treatment group. Because the opening dates of high schools are staggered, I cannot define a unique "before" and "after" period for the control group. Instead, I use a "stacked cohort" approach: a different "before"/"after" dummy variable is created for the control group based on each relevant high school opening year in the treatment group. This way, each high school opening has its corresponding control group with a well-defined period dummy. The data is then "stacked" based on the period dummies.

Table 16: Teacher vs Coworkers Exam Grades

	Teacher Grade Percentile
q2	0.020**
q3	0.034***
q4	0.048***
Small Towns	−0.007
nMedium Towns	0.022
Large Towns	0.056***
q2 × Small Towns	0.004
q3 × Small Towns	−0.006
q4 × Small Towns	0.004
q2 × Medium Towns	0.012
q3 × Medium Towns	0.008
q4 × Medium Towns	0.026
q2 × Large Towns	−0.002
q3 × Large Towns	0.003
q4 × Large Towns	0.017
Subject FE (1+347)	Yes
Year FE (1+4)	Yes
Observations	18,634
Adjusted R^2	0.059

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows the relationship between a new teacher's exam grade and their coworker's average grade.
Small Towns have 2-6 HS, Medium Towns have 7-15 HS, Large towns have 16+ HS; reference level is towns with one high school. Quartiles (q) are teacher exam quartiles within their subject and cohort; reference level is the bottom entrance grade quartile (q1).

Table 17: Teacher vs Student Exam Grades: Regression Results

	Teacher Grade Percentile
Entrance Grade Percentile	0.080^{***}
q2	-0.018^{***}
q3	-0.036^{***}
q4	-0.055^{***}
Small Towns	-0.010^{***}
Medium Towns	-0.057^{***}
Large Towns	-0.056^{***}
q2 × Small Towns	0.005^{***}
q3 × Small Towns	0.004^{***}
q4 × Small Towns	0.007^{***}
q2 × Medium Towns	0.013^{***}
q3 × Medium Towns	0.040^{***}
q4 × Medium Towns	0.078^{***}
q2 × Large Towns	0.008^{***}
q3 × Large Towns	0.046^{***}
q4 × Large Towns	0.094^{***}
Subject FE (1+305)	Yes
Town FE (1+529)	Yes
Year FE (1+5)	Yes
Observations	2,035,048
Adjusted R^2	0.258

Note: *p<0.1; **p<0.05; ***p<0.01.
This table shows the relationship between student entrance scores and teachers working in the same high school's exam scores, by town size. Small Towns have 2-6 HS, Medium Towns have 7-15 HS, Large towns have 16+ HS; reference level is towns with one high school. Quartiles (q) are student entrance exam quartiles within their cohort; reference level is the bottom entrance grade quartile (q1).

Table 18: 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 19: Peer Effects Regression (School Level)

	Dependent variable:					
	Graduation Exam Percentile					
	(1)	(2)	(3)	(4)	(5)	(No HS,HS-Track FE)
Entrance Grade Percentile	0.510***	0.513***	0.513***	0.513***	0.524***	0.524***
	(0.030)	(0.030)	(0.020)	(0.020)	(0.019)	(0.019)
Mean Entrance Percentile (HS)	−0.030	−0.033	−0.012	−0.012	−0.007	−0.007
	(0.031)	(0.030)	(0.026)	(0.026)	(0.022)	(0.022)
Number of High School Students (Town-Yr)	Yes	Yes	Yes	Yes	Yes	Yes
Entrance Decile (Town-Yr) FE (1+9)	Yes	Yes	Yes	Yes	Yes	Yes
Number of HS in Town FE (1+5)	Yes	Yes	Yes	Yes	Yes	Yes
Number of HS in Town × Entrance Decile	Yes	Yes	Yes	Yes	Yes	Yes
Number of HS Students (Town-Yr) × Entrance Decile	Yes	Yes	Yes	Yes	Yes	Yes
HS FE (1+1,470)	Yes	Yes	Yes	Yes	Yes	No
HS-Track FE (8,984)	Yes	Yes	Yes	Yes	Yes	Yes
Town FE (1+557)	No	Yes	Yes	Yes	Yes	Yes
Year FE (1+11)	No	No	Yes	Yes	Yes	Yes
Track FE (1+557)	No	No	No	Yes	Yes	Yes
MS FE (1+19,214)	No	No	No	No	Yes	Yes
Observations	1,187,460	1,187,460	1,187,460	1,187,460	1,187,460	1,187,460
Adjusted R^2	0.620	0.620	0.640	0.640	0.665	0.666

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows the relationship between graduation exam scores and average entrance score of students within high school-year, conditional on own entrance grade. By controlling for high school fixed effects, I identify effects on graduation grades caused by year-to-year variation in high school-level cohort peer ability.

Table 20: Heterogeneity in Peer Effects

	Dependent variable:	
	Graduation Exam Percentile	
Entrance Grade Percentile	0.522***	0.526***
Mean Peer Entrance Percentile	−0.067***	−0.096***
Mean Peer Entrance Percentile × d2	0.012***	0.011*
Mean Peer Entrance Percentile × d3	0.021***	0.027***
Mean Peer Entrance Percentile × d4	0.024***	0.034***
Mean Peer Entrance Percentile × d5	0.029***	0.045***
Mean Peer Entrance Percentile × d6	0.030***	0.056***
Mean Peer Entrance Percentile × d7	0.044***	0.071***
Mean Peer Entrance Percentile × d8	0.058***	0.090***
Mean Peer Entrance Percentile × d9	0.079***	0.113***
Mean Peer Entrance Percentile × d10	0.125***	0.170***
Number of High School Students (Town-Yr)	Yes	Yes
Entrance Decile (Town-Yr) FE (1+9)	Yes	Yes
Number of HS in Town FE (1+5)	Yes	Yes
Number of HS in Town × Entrance Decile	Yes	Yes
Number of HS Students (Town-Yr) × Entrance Decile	Yes	Yes
HS FE (1+1,470)	Yes	Yes
HS-Track FE (8,984)	Yes	Yes
Town FE (1+557)	Yes	Yes
Year FE (1+11)	Yes	Yes
Track FE (1+557)	Yes	Yes
MS FE (1+19,214)	Yes	Yes
Observations	1,182,897	1,187,460
Adjusted R^2	0.665	0.666

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows estimates of hetereogeneity in peer effects, i.e. equation 9, where d is the entrance grade decile (at the high school-cohort and high school-track-cohort levels, respectively).

Table 21: Graduation Grades vs Teacher Ability

	Dependent variable:				
	Graduation Exam Subject Component (Percentile)				
	(1)	(2)	(3)	(4)	(5)
Entrance Grade (Percentile)	0.754***	0.814***	0.801***	0.815***	0.803***
Teacher	0.079***	0.021*	0.026**	0.024*	0.026**
d2 × Teacher		0.009	0.011	0.016	0.015
d3 × Teacher		0.013	0.016	0.018	0.017
d4 × Teacher		0.017	0.020*	0.022*	0.029**
d5 × Teacher		0.023*	0.027**	0.031**	0.039***
d6 × Teacher		0.036**	0.044***	0.048***	0.055***
d7 × Teacher		0.061***	0.067***	0.073***	0.074***
d8 × Teacher		0.084***	0.088***	0.099***	0.098***
d9 × Teacher		0.094***	0.107***	0.117***	0.116***
d10 × Teacher		0.083***	0.098***	0.108***	0.110***
Decile FE (1+9)	No	Yes	Yes	Yes	Yes
Town FE (1+587)	Yes	Yes	Yes	Yes	Yes
Year FE (1+11)	No	Yes	Yes	Yes	Yes
HS FE (1+1,214)	No	No	Yes	Yes	Yes
MS FE (1+12,295)	No	No	No	Yes	Yes
HS-Track FE (1+7,344)	No	No	No	No	Yes
Observations	496,884	496,884	496,884	496,884	496,884
Adjusted R^2	0.483	0.488	0.500	0.523	0.541

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table presents results of individual student graduation subject scores regressed on entrance scores and within-school average subject teacher evaluation scores (Teacher). Interactions between entrance score deciles (d) and teacher ability (Teacher) are also included in order to capture any complementarities between student and teacher ability.

Table 22: Decomposition of Sorting Effects (Second Stage): Track Level

	Dependent variable:					
	Graduation Exam Component Percentile					
	(Baseline)	(Peers)	(Teachers)	(Exp)	(P+T)	(P+T+E)
Adm. Score Percentile (Ro)	0.152***	0.151***	0.160***	0.160***	0.160***	0.160***
Adm. Score Percentile (Math)	0.061***	0.061***	0.076***	0.078***	0.077***	0.078***
Peers (Track)		−0.078***			−0.049***	−0.048***
Teachers			0.097***		0.097***	0.098***
Expenditures				−0.001		−0.002
Instrumented Peer Adm. Score (Track)	0.100	0.075	0.021	0.093	−0.001	−0.008
Number of High Schools in Town	4	4	4	4	4	4
Town-Cohort Adm. Score Decile (d)	10	10	10	10	10	10
Number of Students (Town-Cohort)	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students (Town-Cohort) × d	Yes	Yes	Yes	Yes	Yes	Yes
Town Unemployment Level	Yes	Yes	Yes	Yes	Yes	Yes
County HS Dropout Rate	Yes	Yes	Yes	Yes	Yes	Yes
County Average Wage	Yes	Yes	Yes	Yes	Yes	Yes
Town FE	337	337	337	337	337	337
Year FE	5	5	5	5	5	5

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the county level.
This table shows estimation results of Equation 14, using track peers rather than school peers. It shows the relationship between graduation exam subject scores (e.g. math, Romanian) and school quality, proxied by average admission scores, conditional on own entrance grade. Each column represents a specification in which I add peer effects, teacher ability and/or school expenditure to the baseline model. Number of high schools are grouped into four bins. Town-cohort admissions core deciles (d) are student entrance exam deciles within their town and cohort; reference level is the bottom entrance grade decile (d1). Peer quality is identified by the differences in within-school average admission scores from year to year. Teacher ability is the average placement test percentile of teacher who worked during a student's four year stay, weighted by the number of weekly hours worked. Since I look at graduation exam components separately, onlyteachers teaching relevant subjects are included on the righ-hand side (e.g. math and physics teachers for science component grades). Expenditures are measured in hundreds of Euro/student/year. Peer admission scores are instrumented by an interaction of town-cohort admission deciles and the number of high schools within a town.

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 23 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 23: Statistics Regarding Yearly Match Rates of Graduating and Entering Students

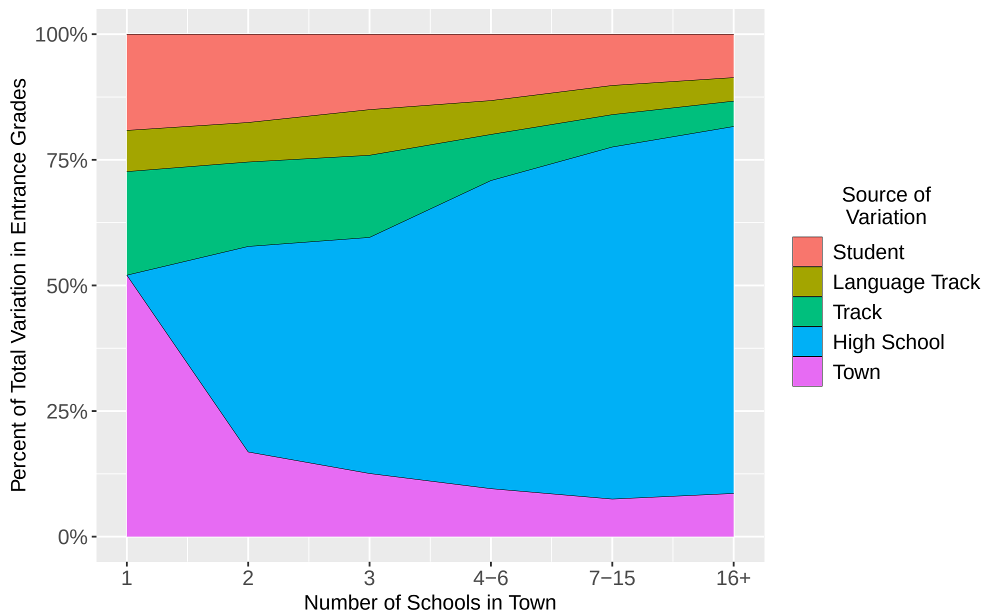
	Min	Q1	Median	Mean	Q3	Max
Graduating Students	56%	59%	64%	66%	71%	75%
Entering Students	48%	52%	59%	59%	66%	67%
Graduating Students (filtered)	58%	64%	79%	74%	84%	85%
Graduating Students (filtered and excluding technical tracks)	67%	73%	84%	80%	85%	86%

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 Notes on Sorting

C.1 Student Sorting

Figure 14: Decomposition of Student Entrance Grade Variance by Town Size



Note: This figure decomposes the variation in student entrance scores into: between student (within track) variation, between track variation (within school), between high school variation (within town) and between town variation, as per Equation 15. The relative contribution of each of these sources is then plotted by town size.

I show that student sorting occurs principally at high school level, rather than at the track or classroom level. I decompose the variation in student entrance scores into different components: between students who choose the same track and foreign language,[42] between different foreign language choices within the same track, between tracks within the same high school, between high schools within the same town and between towns, as follows:[43]

$$\begin{aligned}\sum_{i=1}^{N}(e_i-\mu^e)^2 = &\sum_{i=1}^{N}(e_i-\mu^e_{\text{track}})^2+\sum_{i=1}^{N}(\mu^e_{\text{language-track}}-\mu^e_{\text{track}})^2+\\ &\sum_{i=1}^{N}(\mu^e_{\text{track}}-\mu^e_{\text{hs}})^2+\sum_{i=1}^{N}(\mu^e_{\text{hs}}-\mu^e_{\text{town}})^2+\sum_{i=1}^{N}(\mu^e_{\text{town}}-\mu^e)^2\end{aligned} \tag{15}$$

[42] When applying to high schools, students can submit their preferences at the "classroom" level. More specifically, they can apply to classrooms offering specific tracks (e.g. science, humanities) and specific foreign languages to be taught (e.g. English immersion, German). One can identify which track-language program a student was admitted to in high school using the admission records.

[43] The proof that this equality holds essentially mirrors the proof that $SST = SSR + SSE$ for regressions.

where e is a student entrance grade and μ^e is the average entrance grade.[44] This will make it possible to measure at which level sorting is more prevalent. For example, if students were randomly allocated to schools within towns (and thus there were no school sorting), the fourth component of equation 15 would be close to zero. On the other hand, if students systematically sort into high schools by ability, there would be significant variation in mean entrance scores between high schools and the last component of equation 15 would be large.

In Figure 14, I plot this decomposition of entrance scores for towns of different sizes. The main takeaway is that the proportion of the total variation in grades explained by between-school differences is large and increasing in the number of high schools in a town, as illustrated by the blue area in Figure 14. Indeed, in two high school towns, between high school differences explain just around 40% of the variation in student entrance grades. In contrast, in large cities, more than 70% of the variation in student entrance grades can be explained by differences in average entrance scores between different high schools. In other words, student sorting across high schools increases markedly in the number of schools in a town.

This is consistent with my initial prediction that a relative consensus about the hierarchy of high schools exists and that the degree of student sorting is mostly a function of the number of high school choices available to students.

[44] Unless otherwise specified, all peer averages in this paper are leave-out averages, i.e. they exclude observation i.

Teacher Sorting

I turn towards teacher sorting. In order to better understand to what extent teachers of similar ability sort into schools, I estimate a model relating a teacher's individual ability to the average teacher ability of their coworkers who were hired in the same school:

$$\mu^t_{hy} = \beta_0 + \delta_q + \delta_n + \delta_{q\times n} + \delta_y + \delta_{\text{subject}} + \epsilon_i \tag{16}$$

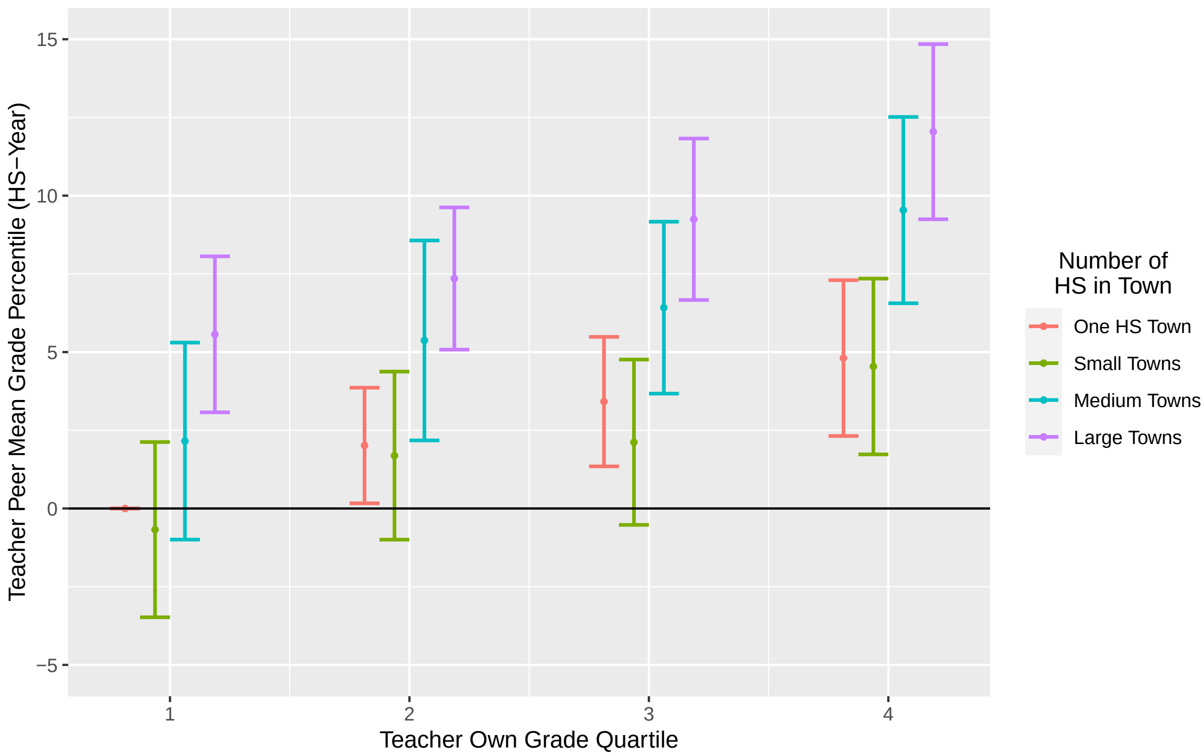
Here, μ^t_{hy} is the average exam score of teachers in high school h and year y. Fixed effects are denoted by δ. I use the following fixed effects: exam decile of teacher i within their cohort and subject, nationally (δ_d), number of high schools in town l where teacher i works (δ_n), the interaction between number of high school and teacher exam score decile ($\delta_{d\times n}$), year (δ_y) and subject (δ_{subject}).

The results of the regression are presented in Table 16 and Figure 15. Teachers who are hired by schools whose other teachers score higher, on average, on the entrance exam also tend to have higher scores. Moreover, teachers hired in larger towns tend to score roughly 6 percentile points higher than those who obtain rural area jobs. Finally, although poorly identified, interaction terms indicate that teachers hired in high teacher entrance score schools in large towns have disproportionately high entrance scores compared to those in high entrance score schools in smaller towns.

On average, teachers hired in top schools in cities score 7 percentiles higher than teachers hired in top schools in small towns. Teachers hired in bottom quartile schools in cities score 6 percentiles higher than teachers hired in bottom schools in small towns. The average difference between top and bottom quartile school hires in cities stands at 6 percentiles. In comparison, this figure is 5 percentiles in one high school towns, highlighting the slightly higher level of teacher sorting in urban areas. In Appendix C, I show more evidence that teacher sorting across high schools is increasing in the number of high schools in towns.

I now show that teacher sorting on ability across high schools is increasing in the number of high schools. In other words, the more high schools there are in a town, the more teachers sort on ability across these high schools. This is especially true for permanent teachers. Thus,

Figure 15: Teacher vs Coworker Exam Grades: Fixed Effects



Note: This figure shows the relationship between teacher own exam grade and average coworker grade within the same school, and how this relationship varies by town size and average teacher ability in the high school. Specifically, it plots $\delta_q + \delta_n + \delta_{q\times n}$ for different combinations of q and n in equation 16. Small Towns have 2-6 HS, Medium Towns have 7-15 HS, Large Towns have 16+ HS.

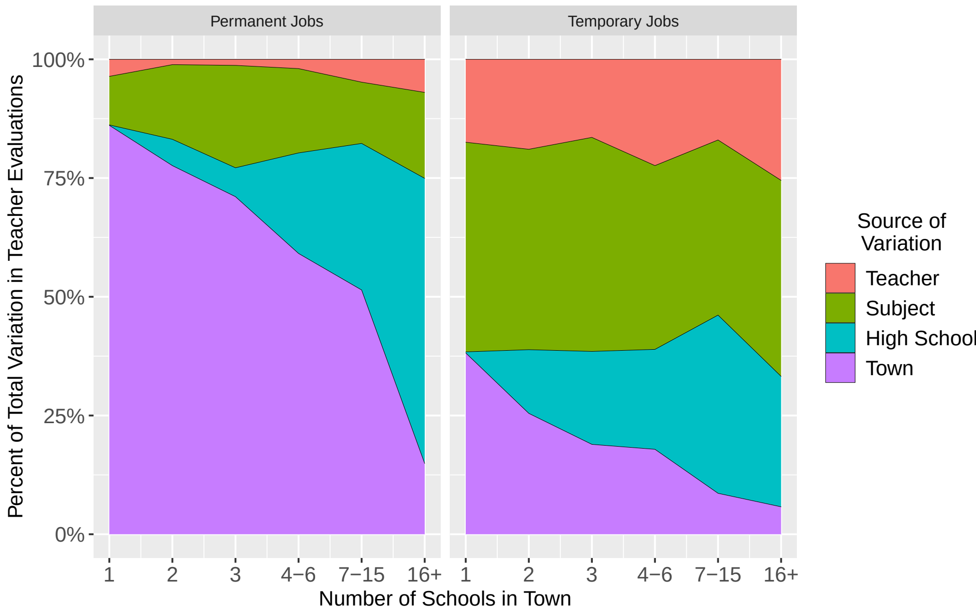
teacher sorting patterns are similar to student sorting patterns: similar-ability teachers tend to cluster into the same high schools and this phenomenon is more prevalent in larger towns.

I decompose the variation of grades into several components: between-teacher variation within the same subject taught and high schools, between subjects within the same high school, between high schools within the same town and across towns:

$$\begin{aligned}\sum_{i=1}^{N}(t_i-\mu^t)^2 = &\sum_{i=1}^{N}(t_i-\mu^t_{\text{subject}})^2+\sum_{i=1}^{N}(\mu^t_{\text{subject}}-\mu^t_{\text{hs}})^2+\\ &\sum_{i=1}^{N}(\mu^t_{\text{hs}}-\mu^t_{\text{town}})^2+\sum_{i=1}^{N}(\mu^t_{\text{town}}-\mu^t)^2\end{aligned} \tag{17}$$

Figure 16 shows that, just like in the case of students, the proportion of the total variation in teacher exam grades explained by between-high school differences is increasing in the number of high schools. This is true for temporary jobs and, to an even larger extent, for permanent teaching jobs. Indeed, in two high school towns, differences in average teacher exam scores

Figure 16: Decomposition of Teacher Exam Grade Variance by Town Size



Note: This figure decomposes the variation in teacher exam scores into: between teacher variation (within subject taught and in the same high school), between subject variation (within high school), between high school variation (within town) and between town variation. The relative contribution of each of these sources is then plotted by town size.

between high schools account for less than 10% (15%) of the total variation in teacher scores for permanent (temporary) jobs. In contrast, for cities, between school differences account for more than 50% (25%) of the total variation in teacher exam scores.

D Identification Concerns and Robustness Checks

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 24. 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 **??** (25). 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 24: 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) × 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 marginal effects from a probit regression of an individual high school drop-out 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 25: 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) $\times$ 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 second stage results form the equation 3. 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 26: 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 3. 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.