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Abstract

This paper investigates the effect of grouping students by prior achievement into different classes in a context where students are preparing for the entrance exams to elite graduate programs offering a limited number of seats. We show that this policy has, on average, positive effects on students' performance and rankings. However, these improvements mainly concern students who were the strongest at the start of the preparation period, among whom children from privileged backgrounds are largely over-represented. Ultimately, the practice of grouping students by prior achievement into different classes increases inequalities in access to elite programs between children from different backgrounds.

JEL Codes: I21, I23, I24.

Keywords: ability tracking, competition, higher education, inequalities.

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1 Introduction

The practice of tracking students by prior achievement into different classes or schools remains extremely controversial in public debate. Creating more homogeneous groups of students allows teachers to better adapt their teaching to the level of their students, which can contribute to improved performance. However, the effects are not necessarily the same for all students, especially when those assigned to lower tracks suffer from less ambitious instruction or less motivated peers. This can lead to an amplification of inequalities in academic performance between the initially weakest and strongest students.

This issue is particularly crucial when tracking is implemented in schools or classes where students are being prepared for high-stakes exams and where students' success ultimately depends on their relative, not absolute, performance. This is the case, for example, when students from different schools or classes prepare to compete for access to highly selective programs, offering a limited number of places, where only the best candidates are admitted, sometimes after a national examination. Such restrictions on the number of seats are implemented in many countries, both at the undergraduate and graduate level, usually for medical, law, or engineering studies.

In such settings, the overall effect of tracking on learning outcomes is of little relevance. If tracking improves the performance of all students to the same extent, it does not affect their ranking, nor does it affect the profile of those who are admitted to the best programs at the end of the preparation years. By contrast, if tracking does not exert the same effect on all students, it can change both their final ranking along with the profile of those students who end up being admitted to the best programs.

In this article, we explore these issues in the context of the two-year undergraduate programs (hereafter, prep schools) that prepare students for competitive entrance exams to the French scientific *Grandes Écoles* graduate programs (hereafter, *GE* programs), one of the historical breeding grounds for the French scientific and managerial elite.[1] A significant fraction of these prep schools group their best first-year students into specific second-year "star" classes and the central question we ask is the effect of this practice on student success.

To approach this question, we first use a database obtained from a specific prep school, with unique information on the performance and choices of students during their prep years. This database enables us to precisely assess the effects of achieving first-year results just above—rather than just below—the threshold for admission into a star class. This regression discontinuity analysis suggests that accessing a

[1]In economics, for example, the four French Nobel Prize winners and the ten former French presidents of the Econometric Society all went to prep schools and are all alumni of one of the two most prestigious GE programs, namely the École Polytechnique or the École Normale Supérieure (ENS, Paris).

star class has a highly significant effect on subsequent performance in the *GE* entrance exams for students close to the admission threshold. In particular, accessing a star class increases by about 50 percentage points the probability that a student reaches the top 10% of all participants to the *GE* entrance exams. Building on Dong and Lewbel (2015), we show that treatment effects derivatives are not statistically different from zero, suggesting that these RDD results can be extrapolated away from the admission threshold.

These first findings are clearly suggestive that the practice of tracking students into different classes is much more favorable to students admitted to the top track than to those relegated to the bottom track. However, because it focuses on a single prep school, this initial analysis may suffer from a lack of external validity. Also, it sheds light on the effect of gaining access to the top track conditional on attending a tracked school, but it says nothing about the effect of attending a tracked school rather than an untracked one. To go further and explore these questions, we use exhaustive administrative databases with information on the local district where students went to high school and on their post high school trajectories. Our identification strategy relies on focusing on students with similar initial academic level (as measured by end-of-high school exam performance) and on comparing those who went to high school in a district that includes a tracked prep school with those who went to high school in a district that includes only untracked prep schools.

The two groups of students appear very similar in terms of their social background and likelihood of persisting until the second year of prep school. However, as expected, the group of students who went to high school near a tracked school is much more likely to enroll in a tracked school than in an untracked one. Among the students who went to high school near a tracked school and who actually persisted until the second year of prep school, we estimate that about one third (hereafter, the compliers) would have enrolled in an untracked school if they had gone to high school in another district, without tracked prep schools.

For those of these compliers who were initially the strongest at the end of high school, increased access to tracked schools essentially translates into an increased access to star classes and into much better performance in the *GE* competitive exams that take place at the end of the preparation period. By contrast, for those of the compliers who were initially the weakest at the end of high school, increased access to tracked schools is primarily followed by an increased relegation to non-star classes in tracked schools. In the end, we see much weaker average improvements in competitive exams performance for this second group of students, in line with the idea that increased access to tracked schools induces improved performance only to the extent that it is followed by an increased access to star classes. As low-income prep students are over-represented among the initially weakest compliers and, consequently, among those who do not access star classes, we also find that inequalities in access to elite graduate programs between students from different social backgrounds are much greater in the districts where the tracked schools are located.

In terms of the mechanisms, our results suggests that an increase in class homogeneity can only improve competitive exam performance if it is achieved by eliminating the initially weakest students and when it is accompanied by an increase in the average level of classmates. Whether they are among the initially strongest or weakest students, our data confirm that those who attend a tracked school all end up in more homogeneous second-year classrooms. However, only those who enter the top track (and can interact with the strongest classmates) take advantage of this when it comes to the final competitive exams.

Our paper contributes to the long-standing debate on the impact of tracking students by prior achievement into different schools or classes. In particular, our RDD analysis contributes to the growing quasi experimental literature exploring the stakes for students of joining the most selective schools or classes rather than the least selective (see e.g., Cullen, Jacob and Levitt, 2006; Hoekstra, 2009; Jackson, 2010; Guyon, Maurin and McNally, 2012; Abdulkadiroğlu, Angrist and Pathak, 2014; Booij, Haan and Plug, 2016; Clark and Del Bono, 2016; Wu, Wei, Zhang and Zhou, 2019; Cohodes, 2020; De Groote and Declercq, 2021). Our comparative analysis of tracked and untracked local districts, in turn, contributes to the more limited literature exploring the stakes for a student of being exposed to local institutions that practice tracking rather than to institutions that do not (Figlio and Page, 2002; Lefgren, 2004; Hanushek and Wößmann, 2006; Duflo, Dupas and Kremer, 2011; Card and Giuliano, 2016; Antonovics, Black, Cullen and Meiselman, 2022). In the context of the undergraduate programs preparing students for entrance exams to elite graduate education, we find that tracking leads to a very significant improvement in prep students' outcomes, but that it primarily benefits prep students who were at the top of the academic performance distribution at the end of high school, thereby contributing to significantly amplifying inequalities in access to elite programs between students initially best and least prepared for higher education.

These results are in line with those put forward by Lefgren (2004) in his analysis of Chicago public schools or by Antonovics, Black, Cullen and Meiselman (2022) in their analysis of the tracking policies implemented in Texan middle schools, even if the institutional context, examination stakes and age of students are completely different. Our findings are also reminiscent of those of Hanushek and Wößmann (2006), who show that inequalities in performance between students tend to increase faster during middle-school years in countries that practice early tracking at the end of elementary school.

However, our results contrast with those obtained by Duflo, Dupas and Kremer (2011) in elementary schools in Kenya, where tracking equally benefits the initially strongest and weakest students. Our results also contrast with those of Card and Giuliano (2016) on tracking in US middle schools because tracking there appears to be more beneficial for minority students. In their experimental study of tutorial groups for first-year economics students at the University of Amsterdam, Booij, Leuven and Oosterbeek (2017) also find that tracking is more effective for students initially at the bottom of the distribution of academic abilities than for those initially at the top of the distribution.

In our context, the aim of teachers is not to get as many students as possible to reach a minimum level and be able to solve the most canonical exercises. The aim is to get students to solve, as quickly as possible, the most difficult problems possible in each chapter of a curriculum that the educational authorities deliberately make excessively heavy. In this particularly competitive environment, the practice of tracking students by prior achievement appears especially beneficial to students who are initially the strongest and best prepared to endure academic pressure and competition.

Finally, our article contributes to the debate about the selection principles of elite educational institutions. Faced with the difficulty of promoting social diversity within elite universities, standardized national competitive examinations have the advantage of implementing transparent criteria and an explicit definition of individual merit. When selection principles are less standardized, the lack of transparency of the procedures feeds recurring accusations of discrimination, such as those that target some of the most prestigious US universities.[2]

However, when competitive examinations prevail, their principle remains controversial and they have long been accused of contributing to the reproduction of elites rather than to their renewal (Bourdieu, 1998). Our work isolates and highlights one of the deep-rooted mechanisms for the reproduction of elites in societies where academic and social success depends on passing competitive exams (including in France, China, India, Japan, Turkey, Russia and many others), namely, that these exams typically involve a long and arduous preparation, the organization of which, often spread across many different prep schools and classes, can contribute to amplifying existing inequalities within localities.

The structure of this paper is as follows. Section 2 describes the institutional framework and presents the data. Section 3 provides the results from our regression discontinuity approach, and Section 4 analyzes the consequences of proximity to a tracked prep school. Finally, Section 5 discusses the mechanisms

[2]On Harvard University's charge that it discriminates against Asian- and African-American applicants, see Arcidiacono, Kinsler and Ransom (2022*a*,*b*). On the mechanisms of discrimination against Jewish students at entrance to elite universities in interwar America, see Karabel (2005).

behind the large positive effects of accessing the top track, and Section 6 concludes.

2 Institutional Context and Data

There are about 235 scientific prep schools in France spread throughout the country. They recruit between 20,000 and 25,000 students each year, that is between 10% and 15% of the students that have just passed their high school exams in science (less than 3% of a given birth cohort). The vast majority of these schools (85%) are public, and tuition fees are almost nonexistent. In addition, most prep schools offer boarding places at unbeatable rates.

After two years of preparation, prep students take competitive entrance exams with the objective of finishing with the best possible ranking. There are more than 200 *GE* programs accessible via competitive exams, but the goal of many prep students is to be ranked in the top 10% so that they can secure admission in one of the Tier 1 programs (among the dozen) that have been feeding the French scientific and economic elite for more than two centuries.

The first year of preparation cannot be repeated and remains relatively generalist, even if a distinction should be made between classes with a Math/Engineering major and classes with Physics/Engineering major or Technology/Engineering major. In the following, we will focus on classes with a Math/Engineering major (called MPSI classes), the most popular. The second year of preparation allows students to refine their specialization. For example, at the end of the first year, students with a first-year Math/Engineering major can either join a second-year class with a Math major (called MP) or a second-year class with an Engineering major (called PSI). Importantly, in many prep schools, the second year also generates a new selection process: the best first-year students are grouped together in "star" classes, while the others have to make do with "non-star" classes. The curricula used for star and non-star classes are similar and the teachers have similarly strong qualifications: they are all chosen from among high-school teachers who finished among the highest-ranked in a national competitive examination (known as the *agrégation*), with a preference for those who have also completed a Ph.D. and have received the best evaluations during their first years of teaching in high school.[3]

The main difference between star and non-star classes is that students in the latter tend to spend more time on the most difficult parts of the curriculum and on the most difficult exercises, to maximize their chances of obtaining admission into the most selective and prestigious *GE* programs. In each prep school, for each major, the numbers of first- and second-year classes are fixed along with the number of

[3]Teachers in prep schools earn a higher salary than high school teachers for fewer teaching hours. They are assigned to the various first-year and second-year classes on a case-by-case basis, depending on the retirement of the most senior incumbents.

star classes, so that the number of first-year students and the proportion of first-year students joining star classes vary very little from one year to the next.

2.1 Detailed data on one specific prep school

Our analysis first uses a dataset providing detailed information on the sample of students admitted to the Math/Engineering first-year prep classes of a specific prep school between 2011-2012 and 2013-2014. This prep school (hereafter, prep school L) is one of the most selective and prestigious of a large French city. It has two first-year classes with a major in Math/Engineering (MPSI classes) and two second-year classes with a major in Math, one star (MP*) and one non-star (MP). At the end of their first year of preparation, students ranked in the upper half of their class join either the MP* class or (for a small minority) the PSI* class of a neighboring prep school that is just as prestigious and selective (hereafter, prep school M). The other half join either the MP class or another non-star class located in other, less selective, prep schools. In our analysis of prep school L, we will define access to a star class as enrollment in the MP* class of prep school L, or enrollment in the PSI* class of prep school M. For each student, we have information on the gender, age, parental income (as measured by eligibility for a means-tested scholarship), and detailed scores from the end-of-high school examinations. We also know student grades at the end of their first year of preparation as well as their first-year official ranking within their class (as shown on their report cards). We also have information on the class in which they are admitted at the end of their first year of preparation (in particular, whether it is a star class or not), and we know if they decide to repeat a year at the end of their second year of preparation, or if they decide to enter a *GE* program. If so, we know the *GE* program they enter. For those who repeat a year, we know the *GE* program they enter at the end of their last year of preparation.

Table A1 in Appendix provides some descriptive statistics about the sample (N=255). These statistics paint the typical picture of one of the most selective prep schools, with many very good students from wealthy backgrounds and very few girls. About 84% of students passed their high school exit exams with the highest honors, compared with only about 15% for all science high school students from the same birth cohorts (see DEPP, 2016). Similarly, the proportion of girls in our sample is 23%, compared with about 45% for all high school science students from the same birth cohorts. Lastly, the proportion of students receiving means-tested financial aid is 15% compared with about 40% students in higher education generally (Dutercq and Masy, 2016). In our empirical analyses, we use information on whether students receive means-tested financial aid to define low- and high-income students.

Figure 1 summarizes students' trajectories in prep program L. About 95% of the students admitted to a star class at the end of the first year subsequently manage to be admitted to a Tier 1 *GE* program compared to only 45% of students admitted to a non-star class at the end of the first year. One of our research questions will be to determine the extent to which this gap in access to Tier 1 programs actually reflects a causal effect of access to the star class on subsequent competitive examination performance.

2.2 Exhaustive administrative data

In addition to the prep school L database, our analysis also relies on an administrative database describing the trajectories of all high school senior students who specialized in science during high school and took their high school exit exams in France between 2010 and 2014. For each student, we know their gender, age and parental income (proxied by their eligibility to means-tested financial aid), as well as the location of the high school they attended, the scores they obtained at the end-of-high school national exams and whether they subsequently entered a prep school. If so, we know the type of prep school and prep classes they enrolled in (and in particular whether the prep school is tracked or not), whether the student was then admitted to a star class in the second year (whether or not the student remained in the same school between the first and second years). Using data on the location of high schools and prep schools, we supplemented this database by constructing a variable indicating for each high school student whether he or she went to high school in a local district that contained a prep school. To define local districts, we relied on the two smallest administrative divisions of the French territory, namely the *communes* and the *cantons*. The largest *communes* are generally covered by several *cantons* and, conversely, many *cantons* cover several small *communes*. We have defined 1604 local districts that correspond to the 223 *communes* that are covered by several *cantons* and the 1381 *cantons* that contain one or more *communes*. Figure A1 shows the division of the French territory into the local districts that we use as well as the location of tracked and untracked prep schools with a second-year Math or Engineering major.

To assess student performance, we obtained administrative data from the statistical services of one of the national competitive examination taken by prep students at the end of their preparation period, namely the *Mines-Ponts* competitive examination. We have information on the performance of all applicants who majored in math or in engineering between 2012 and 2017.[4]

We match this dataset at the individual level with our panel of high school students using information available in both sources, namely information on students' exact date of birth, prep school identifiers,

[4]As explained in greater details in online Appendix B, the *Mines-Ponts* competitive examination is taken by most prep students with a Math or Engineering major (more than 5,000 Math major applicants in 2014) and by nearly all students in prep school L.

majors, star track, scholarship status, and first- or second-time participation status.[5] This enables us to augment our panel of high school students with their results to the *Mines-Ponts* competitive examination (whether or not students repeated the second year of prep school).

Table A2 in Appendix shows descriptive statistics on the characteristics and trajectories of high school students in the science track. The table also shows similar statistics for the subsample of students who took their high school exit exams in a local district with Math or Engineering prep schools (45% of the full sample). The two samples appear quite similar in terms of family background and gender, despite slightly better high school exam results for the students in districts including a prep school. Post high school trajectories are also quite similar across samples: about 5% to 6% of students in the science track enroll and persist to the second year of prep school in the Math or Engineering major, and among them about half attend a tracked prep school and about a third access the top track.

3 The Effects of Accessing the Top Track: a Regression Discontinuity Design

At the end of their first year of preparation, the highest-ranked students from tracked prep schools are admitted into star classes, where they continue their preparation for the competitive entrance exams. In this section, we use the very rich data collected in prep school L to assess the effect of being admitted to a star class on subsequent success in competitive examinations. The advantage of this database is that it contains information on students' class rankings at the end of the first year: by comparing the final outcomes of students whose first-year rankings were just above or just below the threshold for admission to a star class, it is possible to assess the effect of entering a star class with a regression discontinuity method.

3.1 Graphical analysis

Student admission to a star class at the end of the first year of preparation in prep school L depends very directly on their class rank, with only students ranked in the top half of their first-year class having any real chance of being admitted to a star class. To illustrate this, Figure 2 focuses on our three cohorts of prep school L students and depicts the variations in their probability of being admitted to a star class depending on their first-year class rank, the median class rank serving as the origin of the horizontal axis.

The figure confirms that the probability of being admitted to a star class is very low for students

[5]With this procedure, we recover 94% of all France-based applicants in the *Mines-Ponts* competitive examination.

ranked below the median of their first-year class and very high for students ranked above the median. The likelihood of admission jumps by more than 50 percentage points (from about 0.2 to more than 0.7) when we compare students just below the median with those students just above.[6]

In this context, the question becomes whether the average performance of students in the competitive examinations taken at the end of their preparation also varies discontinuously at the median. If this is the case, if there is a coincidence between the point in the class rank distribution where the probability of entering a star class increases and the point where student performance in competitive exams increases, it will provide particularly suggestive evidence on the impact of admission to a star class on performance in competitive exams. To shed light on this issue, Figure 3 shows the variations in the probability of joining a Tier 1 *GE* program as a function of first-year class rank. As explained above, admission to one of these top-ranked *GE* programs is reserved for the top 10% to top 15% of students in the competitive examinations.[7] The figure shows that the probability of entering one of these top programs remains at around 0.45 for students below the median and then jumps twice as high for students just above the median, close to 0.9. Prep school L is one of the most selective in the country, being a prep program in which even students from non-star classes have a high probability of joining a Tier 1 program. However, being admitted to a star class appears to increase this likelihood almost twofold.

In line with this interpretation, Figures A2a to A2d in the Appendix further show that there are no significant discontinuities in the proportion of girls, low-income students or end-of-high school examination results between students just above and just below the median of the first-year ranks. The only observed potential factor of success that increases at the median of the first-year ranks is access to a star class.

3.2 Regression results

Taken together, Figure 2 and Figure 3 suggest very clearly that access to a star class is a decisive factor for success in the competitive exams that determine entry into the most selective *GE* programs. In this subsection, we test the robustness of this graphical results by estimating a regression discontinuity model. Specifically, with variable r denoting the difference between each student's class rank and the

[6]Teachers have some discretion when offering students admission in a star class. This is why we do not observe a 0 to 1 jump in the probability of attending a star class around the median class rank.

[7]The *GE* programs generally considered to be the most prestigious and which we qualify as Tier 1 are the following: *École Polytechnique*, the four *Écoles Normales Supérieures* (*Paris*, *Paris-Saclay*, *Lyon*, *Rennes*), *École Supérieure de Physique et de Chimie Industrielles*, *École Nationale Supérieure des Mines de Paris*, *École Nationale des Ponts et Chaussées*, *École Centrale Paris*, *École Supérieure d'Electricité*, *École Nationale Supérieure des Télécommunications*, *École Nationale Supérieure des Techniques Avancées*, *Institut Supérieur de l'Aéronautique et de l'Espace*, and *École Centrale Lyon*. As explained in Appendix B, this small group of programs recruits the top-ranked students in the three most selective national competitive exams that prep students take at the end of their preparatory years.

median class rank at the end of their first year of preparation, we regress the different outcome variables on a dummy variable Z indicating whether r is positive (i.e., $Z = \mathbb{1}(r > 0)$), using a first-order spline function of r with a knot at $r = 0$ as a control variable. The control variables also include a set of baseline sociodemographic characteristics selected by double lasso, and a set of interactions between year fixed effects and first-year class identifiers. As the treatment (being eligible for a star class) is defined at the individual level, we do not cluster the standard errors (see Abadie, Athey, Imbens and Wooldridge, 2022).

Table 1 details the regression results when we use the same sample as Figure 2 and apply our regression model to the variable describing access to a star class at the end of the first year of preparation, as well as to variables describing the probability of repeating a year at the end of the second year of preparation. Consistent with Figure 2, this analysis confirms that being ranked above the median at the end of the first year (i.e., $r > 0$) very significantly increases (by about 50 percentage points) the probability of entering a star class. Further analysis confirms that this effect reflects an increase in access to the local MP* class (+0.48**), the increase in access to the PSI* class of the neighboring prep program M being much more modest and not significantly different from zero (+0.04). The increase in admission to a star class appears to be at the expense of admission to the local MP class (–0.49**) and only marginally at the expense of admission to a less selective prep program.

Moreover, the model does not reveal any statistically significant discontinuity in the probability of repeating a year at the end of the second year of preparation. Whatever the impact of access to a star class on the type of *GE* programs in which students end up being admitted at the end of their preparation, this effect cannot be interpreted as a consequence of a greater or lesser propensity to repeat a year for the students accessing star classes.

Table 2 applies the same regression model to the variables describing the type of *GE* programs to which students are admitted at the end of their preparation. Consistent with the graphical analyses, the regression results show that being ranked above the median at the end of the first year is followed by a very significant increase in student performance at the end of their preparation. The probability of access to Tier 1 programs is estimated to be nearly 40 points higher for students just above the median, with, at the same time, a quasi-stability of access to Tier 2 programs and a very significant decline in access to other, less prestigious, *GE* programs.[8]

These results are in line with the idea that access to a star class is associated with a general increase in

[8] As explained in online Appendix B, Tier 2 programs correspond to the programs that are ranked just below Tier 1 programs in the *CentraleSupelec* and *Mines-Ponts* competitive examinations. They are as follows: *Ecole Nationale de la Statistique et de l'Administration Economique*, *Ecole Nationale Supérieure des Mines de Nancy*, *Ecole Nationale Supérieure des Mines de Saint-Etienne*, *Ecole Nationale Supérieure des Télécommunications de Bretagne*, *Centrale Nantes*, *Centrale Lille*, *Centrale Marseille*, and *Institut d'Optique Graduate School*.

performance: students who are below the median and who would have been admitted to a Tier 3 program are admitted to a Tier 2 program when they are above the threshold, whereas students who would have been integrated into a Tier 2 program are admitted to a Tier 1 program. Table 2 also confirms that being ranked above the median at the end of the first year increases very significantly the likelihood of scoring among the top 10% of the Mines-Ponts competition (+0.28**).[9]

To take one step further, Table 3 provides an estimation of the causal impact of access to a star class on student performance obtained by using $Z = \mathbb{1}(r > 0)$ as an instrumental variable. Consistent with the first stage and reduced-form estimates in Tables 1 and 2, Table 3 confirms that access to a star class has a major impact on students' performance on entrance exams: it increases the probability of being admitted to a Tier 1 program by 0.7 and that of entering the top 10% of the Mines-Ponts competition by 0.5. Table 3 also shows that these IV estimates tend to be stronger than the OLS estimates, in line with the idea that unobserved determinants of success in competitive examinations tend to be negatively correlated with first-year rankings. This result should be treated with caution, however, as the difference between IV and OLS estimates are not statistically significant at the usual levels.

In this analysis, the identifying assumption is that selection into a star class is the only determinant of student performance that varies discontinuously at the $r = 0$ threshold. To test this hypothesis, Appendix Table A3 provides the results obtained by regressing students' observed baseline characteristics on Z, using the same specification and control variables as for the regression analysis of student performance. None of the estimated regression coefficients are significantly different from zero, in line with our identification hypothesis (and with Figures A2a to A2d). In the same online Appendix, we also build on McCrary (2008) to test for possible manipulation of student rankings around the cutoff. Reassuringly, Figure A4 does not display any significant difference in (log) height at the cutoff.

Given that low-income students have a much lower access to star classes than other students, the existence of these classes (and their very strong impact on performance) ultimately appears to be one of the main factors explaining inequalities in access to Tier 1 programs between income groups. In our sample, only about 46% of low-income group students access a Tier 1 program, compared with 70% of other students, but we can estimate that this 24 percent points gap would be divided by about 3 if the star class access rate of the low-income group were similar to that of the high-income group.

[9] Figure A3 in Appendix shows no discontinuity in student probability of joining the *École Polytechnique* or the *ENS Paris*, suggesting that specific preparation for the most difficult exams is unlikely to explain the positive effects of attending a star class.

3.3 Robustness analysis

Figure A5 and Table A4 show that our RDD results are robust to alternative choices for the bandwidth, or for the set of control variables, or for the specification of the functional form for the running variable. Additionally, to assess the external validity of the star class effects further away above or below the median class rank cutoff, we follow Dong and Lewbel (2015) and compute the treatment effect derivatives (TEDs). Dong and Lewbel (2015) show that a TED equals to zero implies the absence of treatment heterogeneity around the cutoff; by contrast, a positive or negative TED indicates that the estimated treatment effects cannot be extrapolated further away from the cutoff. Appendix Table A5 show that the TEDs for our main performance measures are never statistically different from zero, suggesting that our main results on the effects of being eligible to a star class on exam performance hold for the inframarginal students ranked below or beyond the median. If anything, the direction of the estimated TEDs suggests that gaining access to a star class has marginally stronger effects on the students ranked far above the median (the estimated TEDs tend to be of the same sign as the main discontinuity effects). This is consistent with the idea that students benefit more from the instruction given in the classroom when they are among the best students in that class, in line with Murphy and Weinhardt (2020) or Elsner and Isphording (2017).

4 The Effects of Accessing a Tracked School

Using data from a prep school that tracks its second-year students based on their first-year performance, the previous section suggests that students at this type of school derive significant benefits from being selected into the best classes. However, this result does not mean that students benefit from attending a prep school that tracks its students into different classes rather than a prep school that does not implement such a policy. In particular, it is not clear that attending a tracked prep school is beneficial to the students who do not get into the top track.

In this section, we explore this issue based on the fact that prep schools (whether tracked or not) are scattered throughout the country and almost never switch from being tracked prep schools into being untracked prep schools, or conversely. Our research strategy is based on comparing the performance of prep students who took their high school exit exams in a local district that includes a tracked prep school with those who took these same exams in a local district that only includes untracked prep schools.

4.1 Graphical analysis

To begin with, we consider the full sample of students who took their high school exit exams in the science track between 2010 and 2014 (five cohorts), in a local district in which there is also at least one prep school with a Math or Engineering second-year major. The working sample includes 362,205 high school students from 112 different local districts, of which 36% include a tracked prep school (i.e., a prep school in which first-year students can continue in the second year either in a star or non-star class). Our administrative data provide us with the scores obtained by each of these students during the end-of-high school exams as well as with information on whether they entered a prep school after high school and were able to persist to the second year of preparation (at the end of which students can take the *GE* competitive examinations).

Using this sample and information, Figure 4 plots the probability of entering a prep school and persisting to the second year in the Math or Engineering major (either in the same school or in another one) as a function of the end-of-high school math ranking, separately for students whose high school was located in a district with a tracked prep school and for students whose high school was located in a district with only untracked prep schools. The two curves are superimposed, indicating that obtaining one's end-of-high school degree near a tracked prep school has no effect on the probability of being in a position to take the *GE* competitive exams two years later, regardless of one's initial academic level. In both types of districts, the pattern is almost exactly the same: among the lowest ranked high school students, almost no one can take the *GE* competitive exams two years later, while almost 30% of the highest ranked high school students can.

Based on this first result, we focus on the sample of high school students who enter a prep school and persist to the second-year (Math or Engineering major), so as to compare those who attended high school in a district with a tracked prep school and those who attended high school in a district without tracked prep schools. Using this sample, Figure 5 shows the probability of attending a tracked prep school as a function of end-of-high school within-sample math ranks, separately for the two groups of students.

Unsurprisingly, the probability is significantly higher for those who attended high school in a district with a tracked prep school. The difference in probability between the two types of high school locations is about 25 percentage points for students in the top tercile of the math score distribution and even larger for initially lowest-ranked students. Hence, proximity to a tracked prep school at the end of high school has no effect on the probability of being in position to take the *GE* competitive exams two years later, but as expected, it significantly increases the probability of preparing for these competitive exams at a tracked prep school.

However, proximity to a tracked prep school at the end of high school does not guarantee access to a star class in the second year of preparation: one must also succeed in being among the best first-year students. Using the same sample as Figure 5 (and using the same x-axis), Figure 6 sheds light on this issue by plotting the probability of attending a star class as a function of the students' high school math rank. Again, the probability of accessing a star track is higher for those who attended a high school near a tracked prep school. However, the inter-district gap is now minimal (about 10 percentage points) for the initially lowest ranked prep students and maximal for the highest ranked ones (about 30 percentage points).

Overall, when we compare Figure 5 and Figure 6, we see that proximity to a tracked prep school essentially increases the probability of joining a star class at a tracked prep school for the initially highest ranked students. In contrast, for the initially lowest ranked students, it increases mostly the probability of joining a non-star class at a tracked prep school. Given these facts, we may wonder whether proximity to a tracked prep school increases one's performance at the competitive entrance exams, and whether this effect is the same for the highest and lowest ranked students at the end of high school.

Using the same sample as Figure 5, Figure 7 sheds light on this question by showing the probability of succeeding in being ranked among the top 25% of the Mines-Ponts competition. The figure reveals that coming from a tracked district is unambiguously associated with improved performance, and that this improvement is more significant the higher the initial level of the students. Again, the inter-district gap is minimal (and close to zero) for the initially lowest-ranked students and maximal for the initially highest-ranked students.[10] Taken together, Figures 6 to 7 suggest that access to a tracked school is not in itself a factor for success: the positive effects only materialize for students whose initial academic level allows broad access to a star class.

One immediate consequence is that tracked schools promote the persistence of inequalities across students with different initial academic levels. As shown in Figure 7, the final gap in top performance between the initially best and worst ranked students is actually 33% higher in tracked districts (60 ppt vs. 45 ppt). The broad access to star classes for the initially best-ranked students appears to protect them from competition from the initially less well-ranked outsiders. As discussed below, since low-income students are over-represented among the initially academically weakest students, the existence of a tracked schools in a district is a factor amplifying inequalities in access to elite GE programs between low- and

[10]The same pattern emerges when we analyze the probability of scoring among the top 10% of the Mines-Ponts competition (Figure A6 in the online Appendix).

high-income students.

Before moving on to the regression analysis, it should be emphasized that our analysis of Figures 6 to 7 is based on the assumption that differences in access to tracked schools and star classes are the only differences that can explain differences in achievement between students with the same end-of-high school score but coming from different local districts. Figures A7a to A7e in the online Appendix show how students' age, gender, end-of-middle school score, average end-of-high school score and parental income vary according to end-of-high school math score and type of high school district. In line with our identifying assumption, there is almost no differences in these baseline characteristics across districts, whether we are interested in the initially lowest-ranked students, the initially highest-ranked ones or those initially in the middle of the distribution.

4.2 Regression analysis

The preceding graphical analysis suggests that access to a tracked prep school improves the results of the students who subsequently manage to enter a star class, but not those of the students who are relegated to a non-star class. In this section, we use simple regression models to test the robustness of these findings and further explore the heterogeneity of the effects of access to a tracked prep school. We start by assuming that students' outcomes (denoted Y) can be written:

$$Y_i = \alpha D_i + X_i \beta + u_i \tag{1}$$

where Y_i represents the outcome of student i, while D_i indicates the district where student i did his/her final high school year ($D_i = 1$ if this district contains a tracked prep school, $D_i = 0$ if it only contains untracked prep schools). The variable X_i represents a full set of dummy variables indicating the centile of i's position in the within-sample distribution of end-of-high school math score. We also include controls indicating student i's gender, parental income (scholarship/non-scholarship), age, as well as i's end-of-middle school score and average end-of-high school score.[11] The variable u_i captures the unmeasured resources that can help student i to succeed in the competitive examinations (having parents who have themselves been in prep classes, for example).

The main parameter of interest is α. It captures the reduced-form effect of attending a high school near a tracked prep school rather than near an untracked one. The identifying assumption is that there is no systematic variations in u between the students who attended high school near tracked and

[11] We checked that our results are robust to dropping these additional controls.

untracked prep schools. Table A6 in the Appendix shows the result of regressing students' observed baseline characteristics (gender, age, parental income, academic level at the end of middle school, average high school score) on D. In line with our identification hypothesis (and with Figures A7a to A7e), these balancing checks do not detect systematic significant correlations between students' baseline characteristics and D, regardless of whether we consider our full sample of high school students (Panel A) or the subsample of high school students who enter into a prep school and persist to the second year of preparation in a Math or Engineering major (Panel B).

Table 4 provides our main regression results. The first column of the top panel of Table 4 shows the results obtained with model (1) when Y_i is a variable indicating that student i enters a prep school with a Math or Engineering major and persists to the second year, and when we use the same full sample of high school students as in Figure 4, namely the sample of students who took their high school exit exams in a district in which there is at least one Math or Engineering prep school (whether tracked or not).[12] In line with the previous graphical analysis, the results confirm that geographical proximity to a tracked prep school at the end of high school (as captured by D) has no effect on the probability of being in condition to take the *GE* competitive exams two years later.

Based on this result, the next four columns focus on the subsample of students who enter into a prep school and persist to the second year of preparation (Math or Engineering major). They show the regression results when we use in turn four dependent variables, namely (a) a dummy indicating that students attend a tracked prep school, (b) a dummy indicating that students attend a star class, (c) a dummy indicating that they succeed in being ranked among the top 25% of the Mines-Ponts competitive exams, (d) a dummy indicating that they succeed in being ranked among the top 10% of the Mines-Ponts competitive exams.[13]

The regression results first confirm that proximity to a tracked prep school at the end of high school is associated with a very significant increase in the probability of actually attending a tracked prep school two years later (+30.9 percentage points), as well as with a very significant increase in the probability of attending a star class (+16.3 percentage points). The fact that the first effect is about twice as high as the second one suggests that the students who are geographically induced to attend a tracked prep school (the compliers) have on average roughly a 50/50 chance of entering a star class in their second year of preparation.

[12] Standard errors are clustered at the local district level.

[13] The two last outcomes are measured at the end of the last year of preparation, namely the end of the second year of preparation for students who do not repeat their second year and the end of the third year of preparation for those who repeat their second year.

The regression results presented in Table 4 further confirm that proximity to a tracked prep school at the end of high school (as captured by D) is associated with a significant increase in performance in the Mines-Ponts competitive examination. The estimated effect of D on the probability of scoring among the top 25% of the competition is of 7.7 percentage points (a 34% increase in this probability), while the estimated effect on the probability of finishing among the top 10% is of 4.4 percentage points (a 43% increase).

Taken together, the results in Table 4 confirms that access to a tracked prep school has on average a positive effect on competitive exam performance (in line with Figure 7), but it does not say much about whether the effect is the same when this access is followed by selection into a star class and when this access is followed by relegation into a non-star class. To explore this issue, we augment model 1 with interactions between D and dummy variables indicating students' terciles in the within-sample distribution of high school math scores (Table 4, bottom panel). In line with the previous graphical analysis, the regression results first confirm that D has a stronger impact on access to a tracked school for bottom tercile and medium tercile student compared to top tercile students. In contrast, D has a stronger effect on access to a star class for top tercile and (to a lesser extent) medium tercile students compared to bottom tercile students. Interestingly, we observe the same pattern for the impact of D on competitive exam performance: the positive effects of proximity to a tracked school tend to be much stronger for top tercile and (to a lesser extent) medium tercile students compared to bottom tercile ones. Overall, differences in performance closely parallel differences in access to star classes. The gaps in access to the top 25% of the competition between students in the top or middle terciles and those in the bottom tercile are almost exactly the same as the gaps in access to star classes between these different groups. These regression results are consistent with a model where increased access to tracked schools has a positive impact on performance only insofar as it is followed by an increased access to star classes.[14]

To take a step further, it is possible to assume that proximity to a tracked school at the end of high school (as measured by D) differentially affects students of different initial academic levels only insofar as it differentially affects their access to tracked schools and star classes. Under this maintained assumption, it is possible to identify the causal effect of access to tracked schools and star classes by using the interactions between D and the three dummy variables indicating students' initial academic level as instrumental variables. When we adopt this approach, in line with the previous reduced-form analysis, the estimated IV impact of selection in a star class on the probability of finishing in the top 25% or in the top 10% of the Mines-Ponts competitive exam is positive and large (0.6 for access to the

[14] We have checked that these results are robust to the choice of control variables (see Tables A7 and A8 in online Appendix).

top 10% and 0.9 for access to the top 25%, see Table A9), while the estimated IV effect of relegation to a non-star class at a tracked school is much smaller and negative (about -0.2).

In the end, tracked schools help to raise the level of students who are initially the strongest, but they also contribute to amplifying inequalities between students of different initial academic levels, and consequently (because initial academic level is correlated with social origin) to amplifying inequalities in access to elite programs between students from different social backgrounds.

To illustrate this reality, we can consider prep school students who benefited from a means-tested scholarship in high school, i.e. prep school students who were initially among the poorest. Unsurprisingly, they are largely under-represented among the students who did best in the national exams at the end of high school: there are almost twice as many of them in the bottom than in the top tercile of the distribution of prep students' scores in these exams (46% vs. 24%). They are also much less likely to enter the top 10% of the Mines-Ponts competition at the end of their prep years than non-poor prep students (5% vs 11%). Above all, we checked that this gap in competitive examination success is more than two and a half times greater in districts containing a tracked school than in districts containing untracked schools only (13% vs. 5% in tracked districts and 7% vs. 4% in untracked districts). By grouping in the same classes prep students who have benefited from the best study conditions during high school, tracked prep schools protect them from competition and enable them to further increase their academic advantage over students from disadvantaged backgrounds.

5 Discussion of Potential Mechanisms

A first reason why access to a star class can improve performance is that it may lead to interactions with classmates whose academic level is both more homogeneous and (on average) stronger. As it happens, only the best first-year students are selected in star classes, which mechanically leads to a rise in the minimum academic level of students in these classes. This gives teachers the opportunity to make courses more ambitious, to propose more complex exercises and to focus the preparation on more difficult competitive exams. To illustrate this point, Table A10 in the online Appendix shows the results of regressing a measure of second-year classmates' homogeneity and a measure of their minimal academic level on the variable D which indicates that students' district of origin includes a tracked prep school, as well as on the interactions between D and the terciles indicating the initial academic level of students at the end of high school (i.e., we use the same sample and specification as Table 4, bottom panel). The measure of classmates' homogeneity is the ratio (P10/P90) of the first to the ninth decile of the distribution of second-year classmates' end-of-high school math exam ranks. To measure the minimum academic level of students' classmates we use the first (P10) decile of the distribution. For comparison, we also show the results obtained using the ninth decile (P90) of the distribution. The regression results confirms that proximity to a tracked school (as captured by D) is associated with a significantly stronger increase in the homogeneity of classmates' academic level for initially better ranked students. It also confirms that this effect is driven by an increase in the P10 of the distribution of classmates' academic level, while the P90 is unchanged. This result is consistent with the fact that proximity to a tracked school is accompanied by a much larger increase in access to star classes for initially better ranked students.

Another reason why access to a star class can improve performance is that it can induce a rise in students' expectations and ambitions, leading them to repeat their second year of preparation more often, in the hope of improving their final ranking.[15] If this hypothesis is correct, one of the mechanisms explaining the success of students selected in star classes could be that they tend to retake competitive exams more often than if they had been relegated to a non-star class. To test this hypothesis, we regressed a variable indicating repetition of the second year of preparation on the interactions between the variable D indicating proximity to a tracked school at the end of high school and initial math scores terciles, using again the same sample and specification as in Table 4 bottom panel (see column 4 of Table A10 in the online appendix). The regression results show no significant variation in the impact of D across initial math score terciles, in line with the hypothesis that increased access to star classes has no effect on the probability of repeating the second year of preparation. Among students initially in the top tercile, those who went to high school near a tracked school are much more likely to enter a star class, but they are no more likely to repeat their second year of preparation. Access to a star class does not seem to induce increased perseverance and it does not seem to be through this channel that access to a star class boosts performance.

A last hypothesis is that our results are driven by a few ultra-selective prep schools (such as the one studied in the first part of this article) where a culture and practices conducive to success in competitive examinations have historically been established. To test this hypothesis, we have replicated the analysis of Table 4 bottom panel after removing the prep schools located in Paris and its region (see Table A11 in the appendix) since this is where the most prestigious prep schools are concentrated. We obtain with this restricted sample very similar results to those obtained with the full sample of prep schools, in line with the idea that our main results are not specific to Paris and its surroundings.

[15] Students who choose to repeat the second year of preparation do not keep the admissions they obtained during their first participation in the competitive entrance exams. However, it is very rare that their ranking does not improve after an additional year of preparation (Landaud and Maurin, 2020).

6 Conclusion

France's *Grandes Ecoles* have been the cradle of French academic and managerial elites for over two hundred years. Entrance examinations to these programs are highly selective and take place over a two-year period at prep schools that can be accessed after high school. About a third of these prep schools group their best first-year students into specific second-year star classes and our paper explores the effect of this tracking practice on student success. The scattering of tracked and untracked prep schools across the country is a legacy of history, and it is almost never the case that a school changes its organization from one year to the next.

To assess the importance of this policy, we first use data from a specific (tracked) prep school, with rich information on prep students' outcomes during their prep years. This data allows us to compare students whose first-year results are either just above or just below the local threshold for admission into a star class. This regression discontinuity analysis is suggestive that accessing a star class has a very strong effect on subsequent performance in the *Grandes Ecoles*' entrance exams. Accessing a star class increases by about 50 percentage points the probability that a student reaches the top 10% of all participants to the entrance exams.

To go further, we use exhaustive administrative data to compare the performance of students depending on whether they went to high school in a district containing a tracked prep school or in a district containing only untracked prep schools. For students who were initially the strongest in high school, proximity to a tracked prep school appears to increase strongly the probability of access to a star class and the likelihood of scoring high at the most prestigious competitive exams. For students who were initially the weakest in high school, proximity to a tracked prep school mainly increased the probability of finishing their preparation in a non-star class of a tracked prep school, with no significant effect on competitive exam success. These findings are suggestive that increased access to tracked schools induces improved performance in competitive exams only to the extent that it is followed by an increased access to star classes. In the end, the practice of grouping students by prior achievement contributes significantly to amplifying the academic inequalities that pre-exist when students arrive at prep schools, with the indirect consequence of amplifying inequalities in access to elite programs between children from different social backgrounds.

In most countries, students from disadvantaged backgrounds are underrepresented in elite institutions of higher education, even when recruitment is done through standardized competitive examinations, as in France, Japan, India, and China. Advocates of such competitive procedures argue that the problem is not with the principle of competitive examinations, but with the fact that too few students from disadvantaged backgrounds survive school selection long enough to be able to even start preparing for these difficult examinations. Our research suggests that there is also a problem with the entrance exams themselves, particularly because they typically require years of intense preparation, and not all students are initially equally equipped for the efforts required and have access to the same preparation programs.

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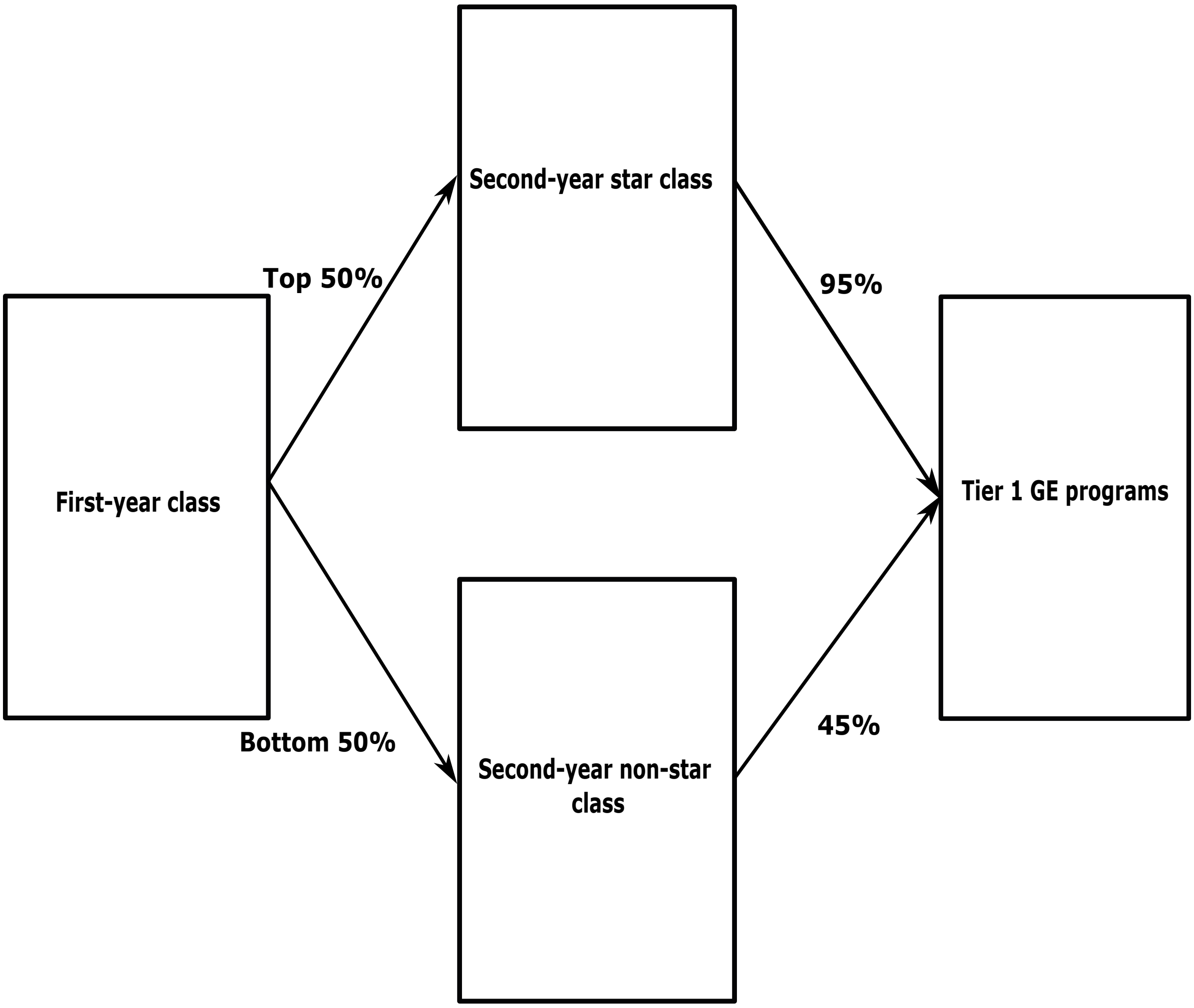


Figure 1: Schooling trajectories of students enrolled in prep program L

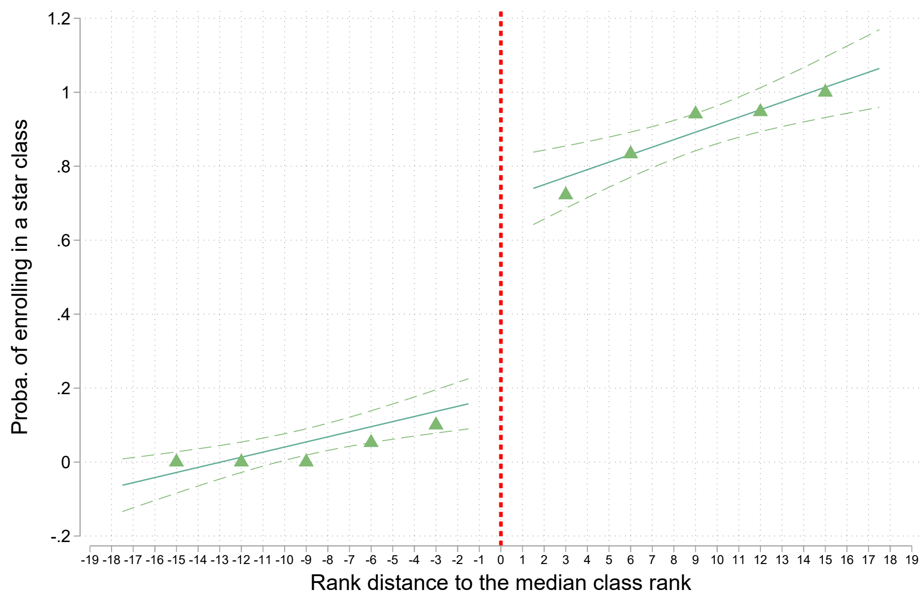


Figure 2: End-of-first-year ranking and admission to star classes

Notes: The figure refers to the sample of first-year students in prep program L whose first-year final ranking fell within –20 to +20 seats of the median rank in their class (excluding students within –1 to +1 seats). The figure shows the proportion of students who enroll in a star class during the second year, plotted against their final ranking at the end of the first year (with the median class rank as the origin).

In detail, the solid line plot the fitted regression line after estimating the relationship between star class enrollment and whether students' class rank is above the median class rank, while controlling for a first-order spline function of students' class rank (without any other controls for student baseline characteristics). The plotted points are the conditional means of the dependent variable for students in binwidth of 3-ranks.

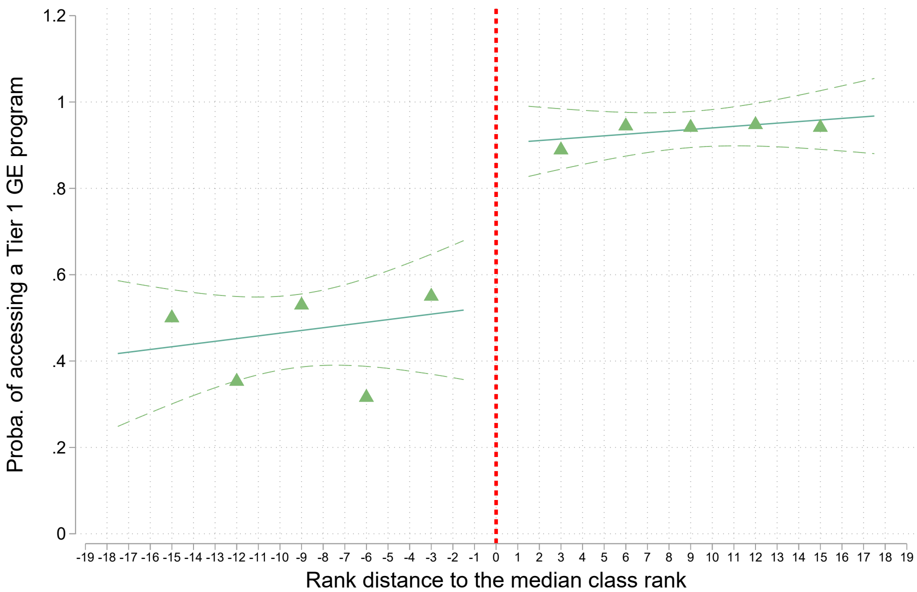


Figure 3: End-of-first-year ranking and admission into Tier 1 *GE* programs

Notes: The figure refers to the same sample as Figure 2 and uses the same specification. The figure shows the proportion of students admitted to Tier 1 *GE* programs (*École Polytechnique*, the four *ENS*, *ESCPI*, *Centrale Paris*, *Supelec*, *Centrale Lyon*, and the five most selective schools of the Mines-Ponts competition), plotted against their final ranking at the end of the first year (with the median class rank as the origin). Below the median, about 50% of students are admitted to a Tier 1 program, whereas this proportion exceeds 90% above the median.

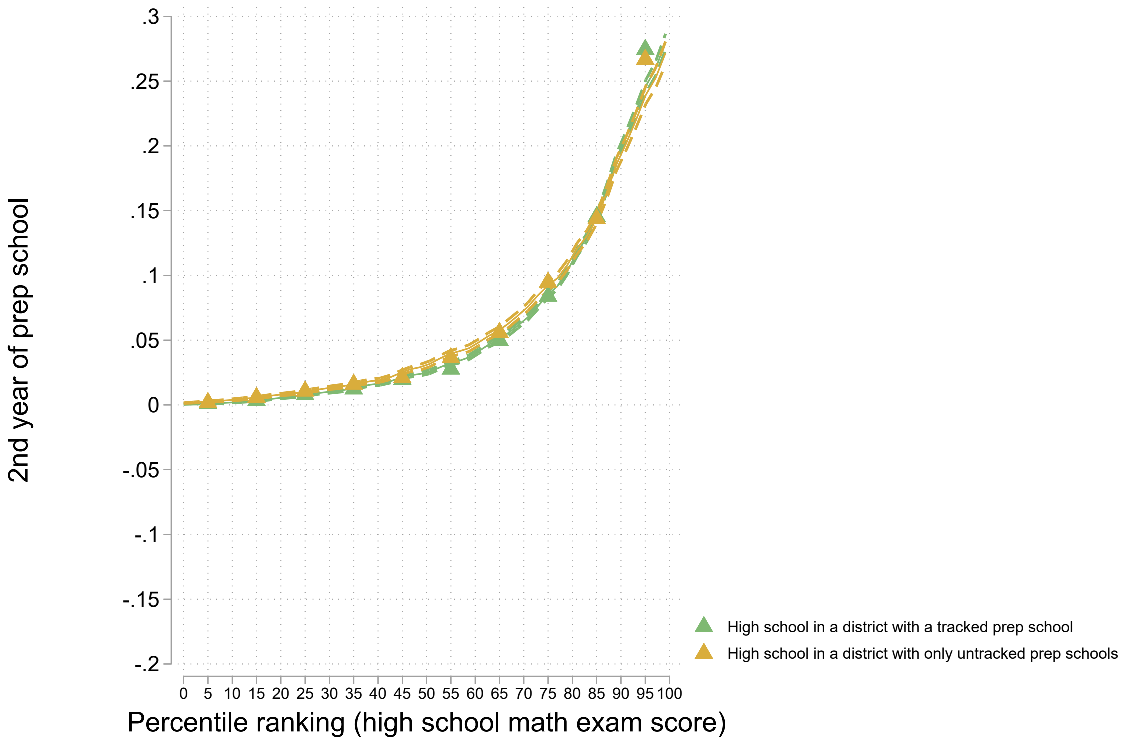


Figure 4: Proximity to tracked prep schools, baseline ability, and probability of persisting until the 2nd year of prep school

Notes: The figure refers to the sample of students who took their high school exit exams in science between 2010 and 2014, and whose high school was located in a local district with tracked or untracked prep schools offering a Math or Engineering major. The figure displays the proportion of students who attend a prep school and persist until the second year in the Math or Engineering major as a function of their percentile end-of-high school math exam ranking. It shows results separately for students whose high school local district contains a tracked Math or Engineering prep school and for those whose district contains only untracked prep schools.
In both types of districts, almost 30% of the highest-ranked students enroll and persist until the second year of prep school in the Math or Engineering major, while almost none of the lowest-ranked students do so.

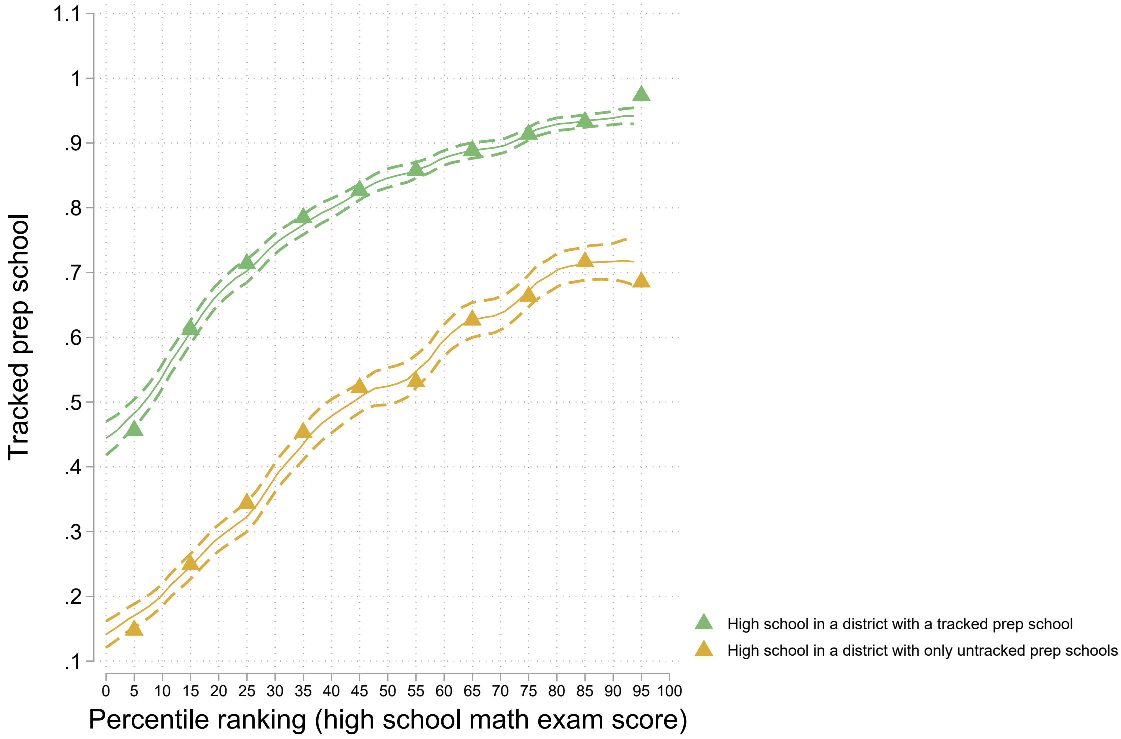


Figure 5: Proximity to tracked prep schools, baseline ability, and probability of attending a tracked prep school

Notes: The figure refers to the same sample of students as Figure 4, restricted to the students who attended a prep school and persisted to the second year in the Math or Engineering major. The figure displays the proportion of students whose prep school (defined as the school they attended during their first year) offers star classes in the Math or Engineering major, as a function of their withn-sample percentile end-of-high school math exam ranking. It shows results separately for students whose high school local district contains a tracked Math or Engineering prep school and for those whose district contains only untracked prep schools.
Spending the high school senior year in a district with tracked prep schools increases the likelihood that students enroll in such schools rather than in untracked prep schools. Furthermore, the difference between the two types of districts is more pronounced at the bottom of the distribution (+30 percentage points) compared to the top of the distribution (+20 percentage points).

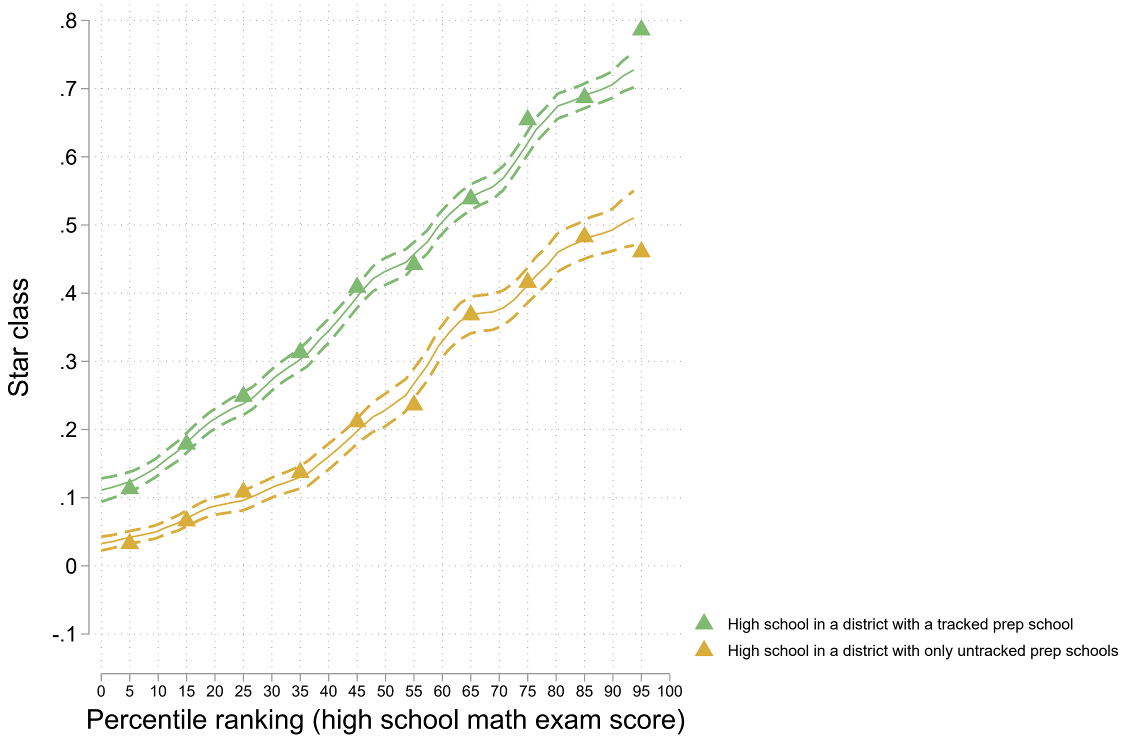


Figure 6: Proximity to tracked prep schools, baseline ability, and probability of attending a star class

Notes: The figure refers to the same sample of students as Figure 5. The figure displays the proportion of students who attend a star class in the Math or Engineering second-year majors, as a function of their within-sample percentile end-of-high school math exam ranking. It shows results separately for students whose high school local district contains a tracked Math or Engineering prep school and for those whose district contains only untracked prep schools.

Spending the high school senior year in a district with tracked prep schools increases the likelihood that students enroll in a star class. Moreover, the difference between the two types of districts is more pronounced at the top of the distribution (+20 percentage points) compared to the bottom of the distribution (+5 percentage points).

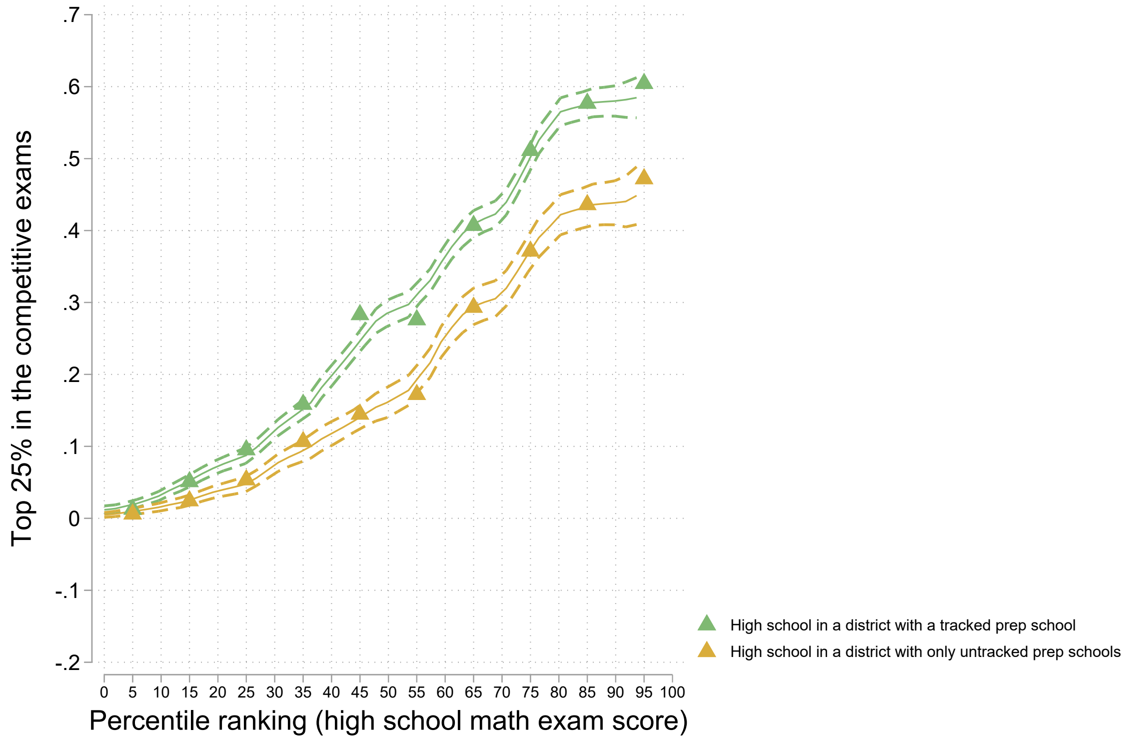


Figure 7: Proximity to tracked prep schools, baseline ability, and probability of scoring among the top 25% in the competitive exams

Notes: The figure refers to the same sample of students as Figure 5. The figure displays the proportion of students who score among the top 25% of applicants during the Mines-Ponts competitive examinations, as a function of their within-sample percentile end-of-high school math exam ranking. It shows results separately for students whose high school local district contains a tracked Math or Engineering prep school and for those whose district contains only untracked prep schools.
Spending the high school senior year in a district with tracked prep schools increases the likelihood that students score in the top 25% of the Mines-Ponts competition. In addition, the difference between the two types of districts is more pronounced at the top of the distribution (+15 percentage points) compared to the bottom of the distribution (no significant differences).

Table 1: Effects on access to a star class of falling above the first-year median class rank: a regression discontinuity analysis

	Coeff.	Mean below the median class rank	N
Type of track after the 1st year			
Star class	0.526***	0.106	193
	(0.078)		
-at prep school L (MP*)	0.483***	0.000	193
	(0.085)		
-at prep school M (PSI*)	0.044	0.106	193
	(0.082)		
-non star class at prep school L (MP)	-0.487***	0.745	193
	(0.119)		
Other prep programs	0.015	0.106	193
	(0.084)		
Other fields	-0.056	0.043	193
	(0.042)		
Repetition after the 2nd year	-0.056	0.340	193
	(0.137)		

Notes: The table refers to the same sample of students as Figure 2. Each row corresponds to a specific dependent variable, namely a dummy variable indicating admission to a star class (MP* in prep program L or PSI* in prep program M) after the first year of preparation (row 1), a dummy indicating admission to a star class in the MP track at prep program L (row 2), a dummy indicating admission to a star class in the PSI track at the neighboring prep program M (row 3), a dummy indicating admission to a non-star class in the MP track at prep program L (row 4), a dummy indicating admission to other prep programs in the Math or Engineering track (row 5), a dummy indicating admission to other studies (row 6), and a dummy indicating year repetition at the end of the second year (row 7). For each dependent variable, the first column shows the estimated impact of falling just above the median class rank during the first year of preparation. Standard errors are in parentheses, and all regressions include controls selected by the double lasso approach among student high school graduation results, first-year results, age, gender, low-income status, boarding status; a full set of class#year dummies; and a first-order spline function of the running variable. The second column shows the mean of each dependent variable for students whose first-year final ranking fell just below the median rank of their class (within –9 to –1 seats), and the third column shows the number of observations. This table shows, for example, that the probability of students being admitted to a star class increases by about 53 percentage points just above the median class rank.
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table 2: Effects on exam performance of falling above the first-year median class rank: a regression discontinuity analysis

	Coeff.	Mean below the median class rank	N
Tier 1 *GE* program	0.372***	0.489	193
	(0.124)		
Tier 2 *GE* program	-0.066	0.170	193
	(0.101)		
Other *GE* program	-0.257***	0.255	193
	(0.096)		
Other field of study	-0.048	0.085	193
	(0.065)		
Top 25% in the competitive exams	0.059	0.723	193
	(0.118)		
Top 10% in the competitive exams	0.275**	0.170	193
	(0.134)		

Notes: The table refers to the same sample of students as Figure 2. Each row corresponds to a specific dependent variable characterizing student performance during the competitive exams, namely, a dummy indicating admission to a Tier 1 *GE* program (row 1), a dummy indicating admission to a Tier 2 *GE* program (row 2), a dummy indicating admission to a less prestigious *GE* program (row 3), a dummy indicating other types of studies (row 4), a dummy indicating whether students scored within the top 25% of the Mines-Ponts competition (row 5), and a dummy indicating whether students scored within the top 10% of the Mines-Ponts competition (row 6). For each dependent variable, the first column shows the estimated impact of falling just above the median class rank during the first year of preparation. Standard errors are in parentheses, and all regressions include controls selected by the double lasso approach among student high school graduation results, first-year results, age, gender, low-income status, boarding status; a full set of class#year dummies; and a first-order spline function of the running variable. The second column shows the mean of each dependent variable for students whose first-year final ranking fell just below the median rank of their class (within –9 to –1 seats), and the third column shows the number of observations. This table shows, for example, that the probability of students being admitted to a Tier 1 *GE* program increases by about 37 percentage points, and that of being admitted to a Tier 2 *GE* program (i.e., the four least selective schools of the Mines-Ponts competition, the schools "*Centrales*" outside of Paris and Lyon, and *SupOptique*) decreases by about 7 percentage points.
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table 3: Effect of enrolling in a star class on student performance (LATE vs OLS)

	LATE	OLS
Tier 1 *GE* program	0.706***	0.435***
	(0.246)	(0.061)
Top 10% in the competitive exams	0.523**	0.355***
	(0.266)	(0.069)
N	193	193

Notes: The table refers to the same sample of students as Figure 2. The table compares the estimated effects of enrolling in a star class on student exam performance using a regression discontinuity design approach (where we instrument enrollment in a star class by being above the class median rank, column 1), or using a linear model (column 2).
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table 4: Tracked prep schools, star classes, and competitive exam performance

	Outcomes				
	2^{nd} year of prep school	Tracked prep school	Star class	Top 25% competitive exams	Top 10% competitive exams
Baseline specification					
High school in a district with a tracked prep school	-0.003	0.309***	0.163***	0.077***	0.044***
	(0.003)	(0.040)	(0.026)	(0.025)	(0.016)
Adding interractions with students' baseline ability					
High school in a district with a tracked prep school	-0.004**	0.345***	0.107***	0.020	0.008
	(0.002)	(0.048)	(0.021)	(0.014)	(0.006)
HS in a district with a tracked prep school#Medium baseline ability	0.004	-0.021	0.075***	0.069***	0.037***
	(0.007)	(0.024)	(0.025)	(0.021)	(0.012)
HS in a district with a tracked prep school#Top baseline ability	0.014	-0.095***	0.102***	0.111***	0.079***
	(0.012)	(0.035)	(0.034)	(0.027)	(0.028)
Mean dep. var.	0.061	0.661	0.336	0.233	0.105
N	362205	22075	22075	22075	22075

Notes: The table refers to the sample of students who took their high school exit exams in science between 2010 and 2014, and whose high school was located in a local district with tracked or untracked prep schools offering a Math or Engineering major (column 1). Columns 2 to 4 are further restricted to the students who attended a prep school and persisted until the second year in the Math or Engineering major. In the top panel, each column corresponds to a specific regression, and reports the estimated impact of spending the high school senior year in a local district with tracked prep schools rather than in a local district with only untracked prep schools on the dependent variable mentioned above. In the bottom panel, the analysis is augmented by interactions between the type of high school local districts and students' terciles in the distribution of high school math exam scores. Each regression includes a full set of dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution and cohort fixed effects, as well as additional controls for students baseline characteristics (middle school and end-of-high school average scores, age, gender and low-income status). For columns 2 to 4, students' rankings are defined within our working sample of students who enroll in prep school and persist until the second year in the Math or Engineering major. Standard errors clustered at the local district level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Appendix A

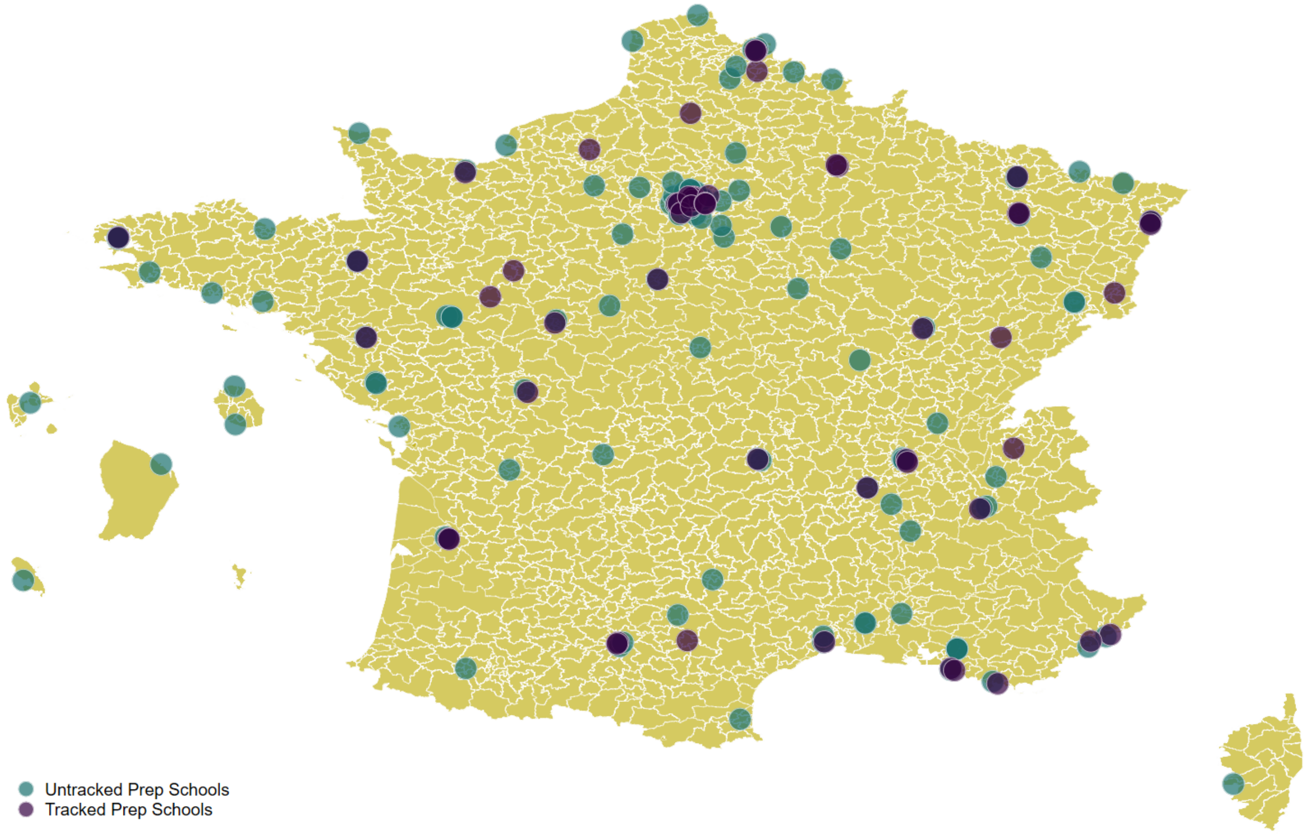


Figure A1: Local districts in France and geographic localization of Math and Engineering prep schools

Notes: The figure shows the 1,604 local districts considered in the empirical analysis. These local districts consist of 1,381 areas (referred to as “cantons”) that group small municipalities, and 223 areas (referred to as "cantons fractionnés") combined together as they cover the same large municipality. The figure also display the localizations of prep schools offering Math or Engineering second-year majors, separately for tracked and untracked prep schools.

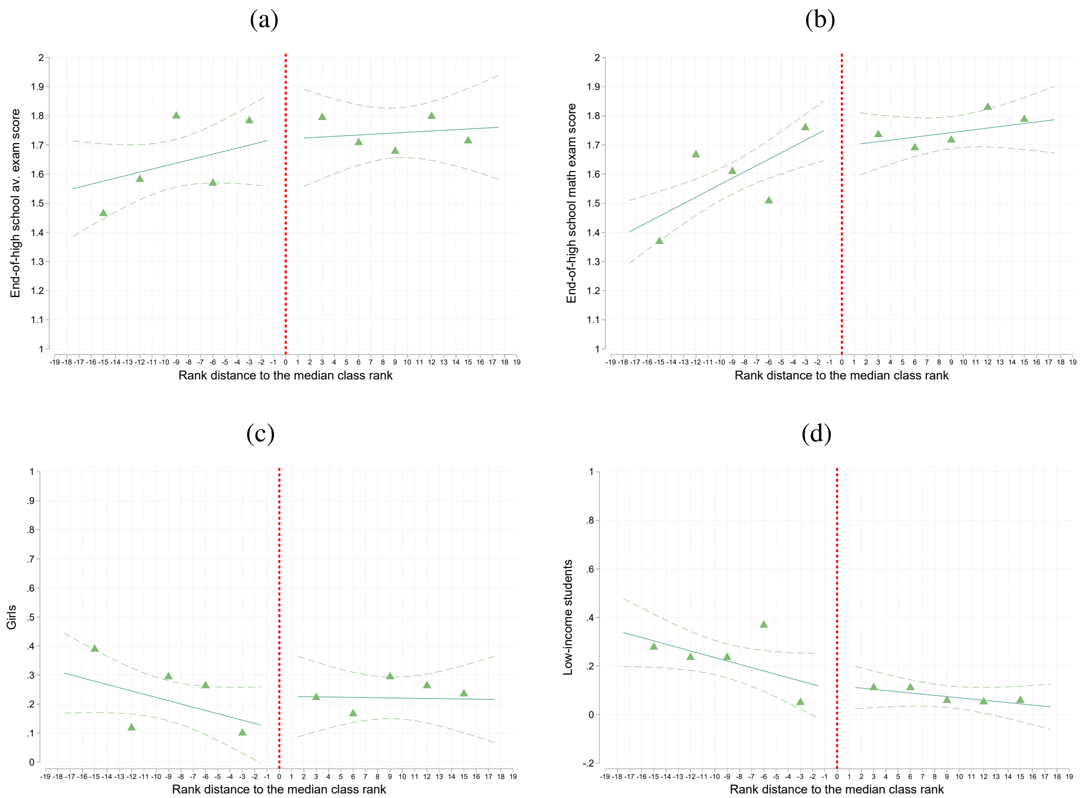


Figure A2: End-of-first-year ranking and student baseline characteristics

Notes: The figure refers to the same sample as Figure 2 and uses the same methodology. The figure shows student baseline characteristics (high school graduation results, gender, and low-income status), plotted against their final ranking at the end of the first year (with the median class rank as the origin). The higher a student's first-year final ranking, the lower the proportion of low-income students, with about 30% of low-income students among those with the lowest ranks and almost none among those with the highest ranks.

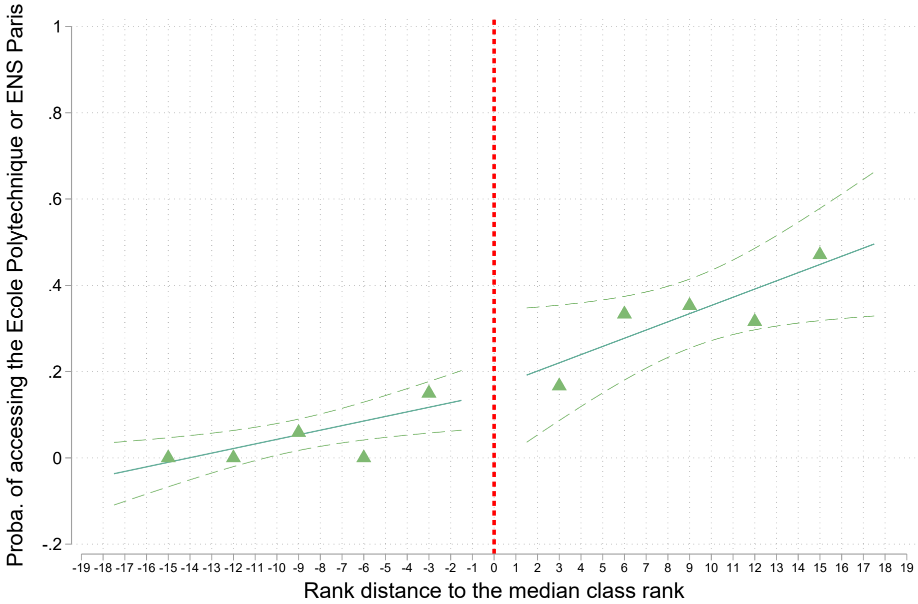


Figure A3: End-of-first-year and admission into the top two *GE* programs

Notes: The figure refers to the same sample as Figure 2 and shows the proportion of students admitted to the *École Polytechnique* or the *ENS Paris*, plotted against their final ranking at the end of the first year (with the median class rank as the origin). Just above and below the median, about 20% of students are admitted to the top two *GE* programs.

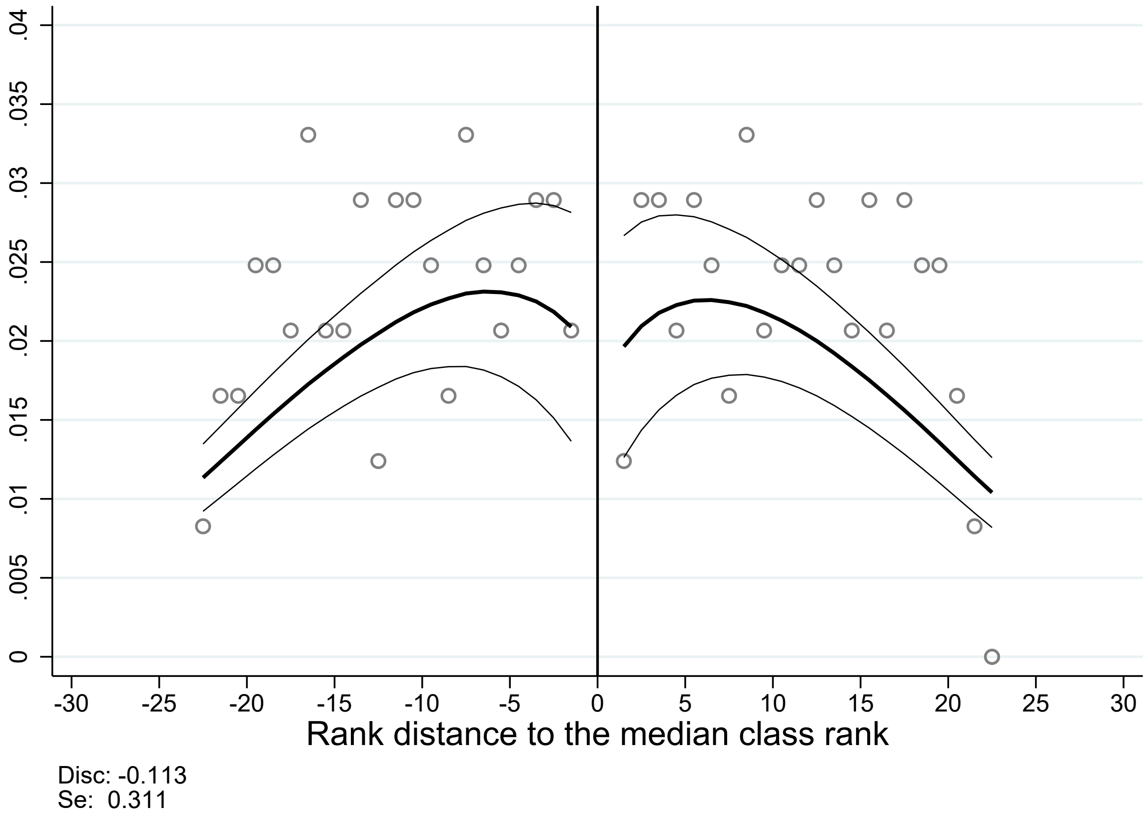
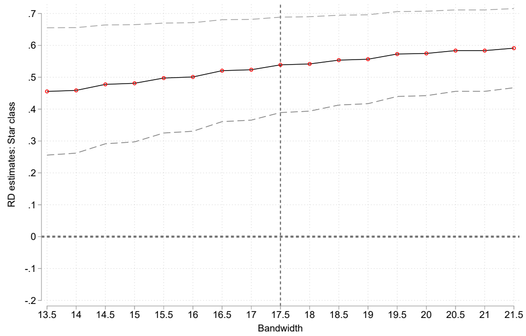


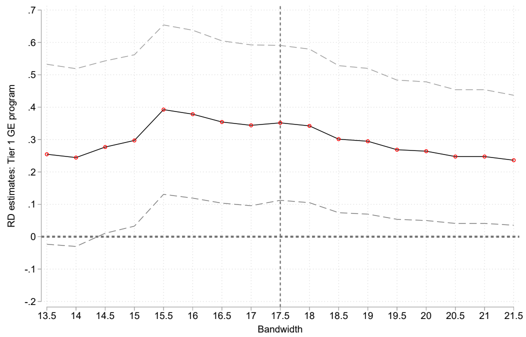
Figure A4: Density of observations around the median class rank

Notes: The figure refers to the same sample as Figure 2. The figure presents nonparametric estimates of the density of observations on either side of the admission thresholds following McCrary (2008). Each circle shows the average frequency of students per bin of the running variable. The solid lines represent estimated density functions, and the dashed lines represent the corresponding 95% confidence intervals. The bottom left of the figure reports the estimated discontinuity for the density at the cutoff with its standard errors.

(a) Probability of being admitted to a star class



(b) Probability of being admitted to a Tier 1 *GE* program



(c) Proba. of scoring among the top 10% in the competitive exams

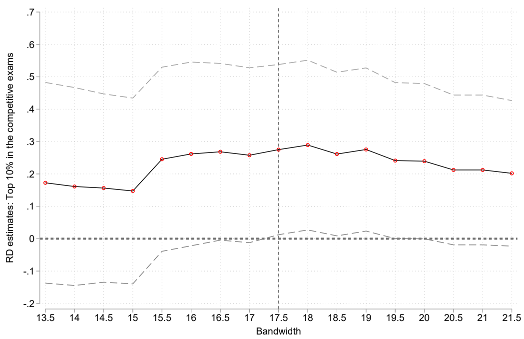


Figure A5: Robustness to bandwidth selection

Notes: The figure refers to the same sample as Figure 2. The figure shows the estimated effect of falling just above the median class rank on four different outcomes with varying bandwidths. (a) presents the estimated effect of falling just above the median class rank on the probability of being admitted to a star class, (b) presents the estimated effect on the probability of being admitted to a Tier 1 *GE* program, and (c) reports the estimated effect on the probability of scoring among the top 10% of the Mines-Ponts competition. The solid red line represents the point estimates using the same specification and control variables as in Tables 1 and 2. The vertical line shows the bandwidth used in the main analysis. The dashed lines represent 95% confidence intervals.

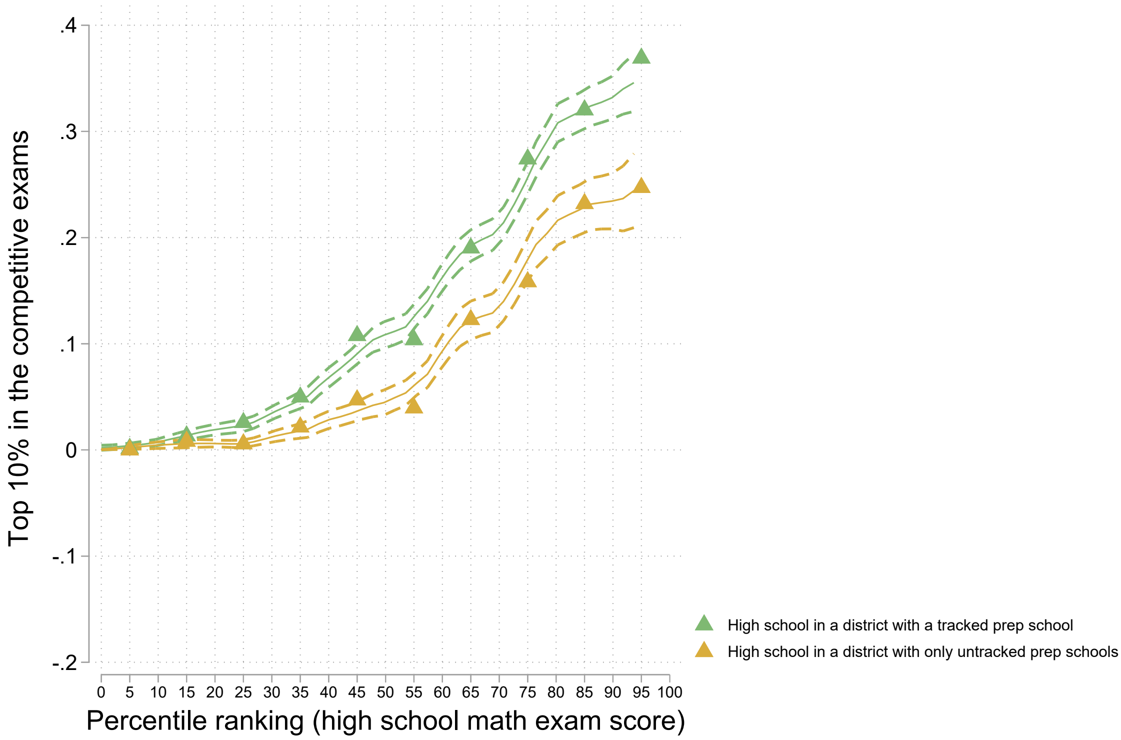


Figure A6: Proximity to tracked prep schools, baseline ability, and probability of scoring among the top 10% in the competitive exams

Notes: The figure refers to the same sample of students as Figure 5. The figure displays the proportion of students who score among the top 10% of applicants during the Mines-Ponts competitive examinations, as a function of their within-sample percentile end-of-high school math exam ranking. It shows results separately for students whose high school local district contains a tracked Math or Engineering prep school and for those whose district contains only untracked prep schools.
Spending the high school senior year in a district with tracked prep schools increases the likelihood that students score in the top 10% of the Mines-Ponts competition. In addition, the difference between the two types of districts is more pronounced at the top of the distribution (+10 percentage points) compared to the bottom of the distribution (no significant differences).

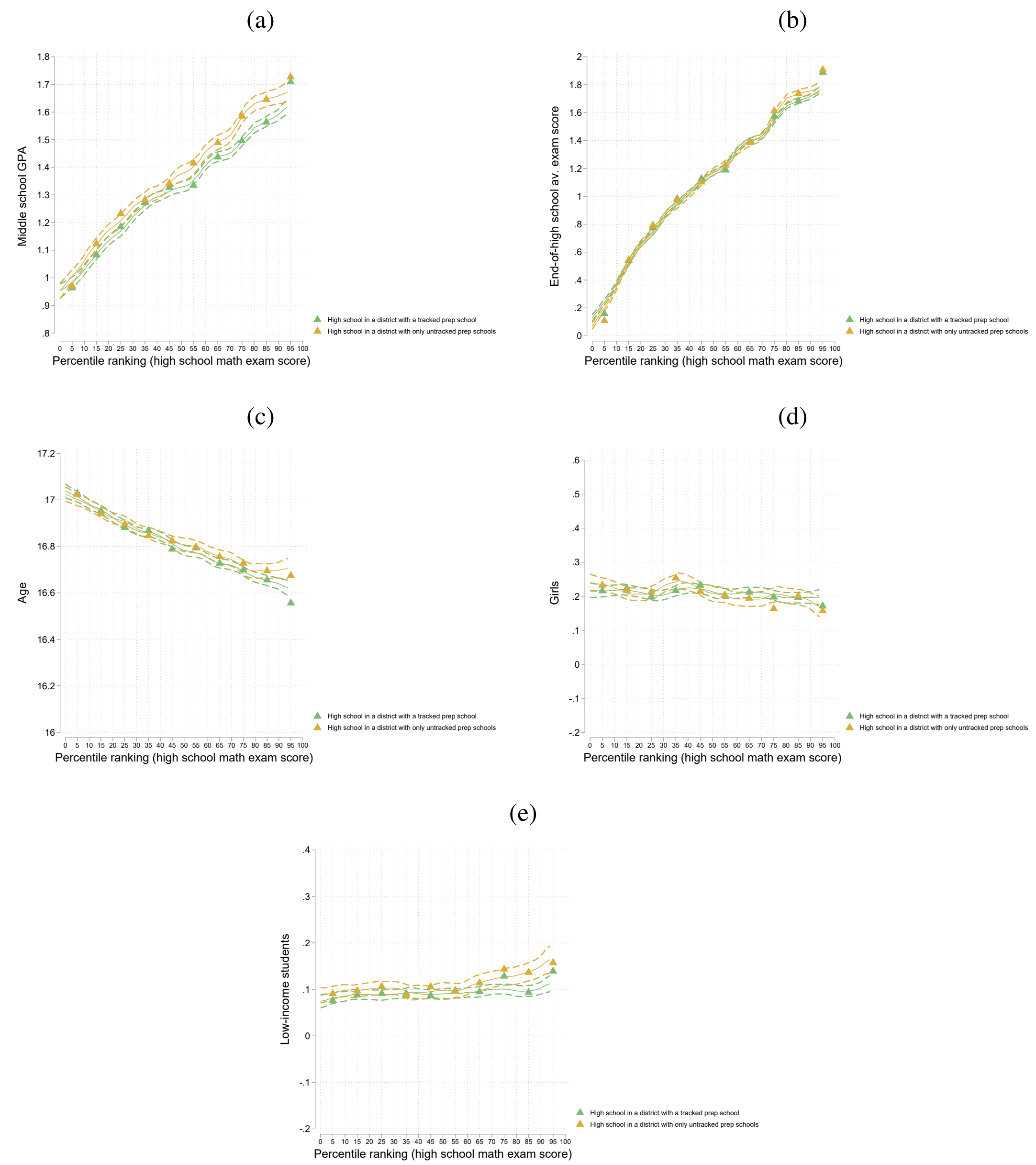


Figure A7: Proximity to tracked prep schools, baseline ability, and students' baseline characteristics

Notes: The figure refers to the same sample of students as Figure 5. The figure displays the baseline characteristics (middle school and end-of-high school average scores, age, gender and low-income status) of the students in our working sample, depending on their percentile within-sample end-of-high school math exam ranking. It shows results separately for students whose high school local district contains a tracked Math or Engineering prep school and for those whose district contains only untracked prep schools.

Students' baseline characteristics vary by baseline ability: the highest ranked students in math also have better end-of-middle school and end-of-high school scores, and they are less likely to have repeated a year. However, conditional on baseline ability, students' characteristics do not vary significantly across the two types of high school districts.

Table A1: Descriptive statistics on the students in prep program L

High school grad. with high honors	0.839
	[0.368]
End-of-high school av. exam score	1.65
	[0.53]
End-of-high school math exam score	1.62
	[0.38]
Age < 18 at entry	0.33
	[0.47]
Girls	0.23
	[0.42]
Low-income students	0.15
	[0.35]
Boarders	0.16
	[0.37]
Observations	255

Notes: The table refers to all students enrolled in the first year of prep program L (Math/Engineering classes) between 2011–2012 and 2013–2014, and describes their baseline characteristics, namely their high school graduation results (rows 1 to 3), their age (row 4), their gender (row 5), their low-income status (row 6), and their boarding status (row 6).

Table A2: Descriptive statistics for the empirical analysis on tracked schools and star classes

	All high school students in the Science track	Students whose high school is located in a district with a Math or Engineering prep school
Middle school GPA	0.971	0.977
	(0.548)	(0.553)
End-of-high school math exam score	0.012	0.094
	(0.988)	(0.995)
End-of-high school av. exam score	0.058	0.133
	(0.910)	(0.923)
Age	17.144	17.134
	(0.630)	(0.642)
Girls	0.456	0.454
	(0.498)	(0.498)
Low-income students	0.122	0.114
	(0.328)	(0.318)
2^{nd} year of prep school	0.051	0.061
	(0.219)	(0.239)
Observations	802,298	362,205
Tracked prep school	0.496	0.494
	(0.500)	(0.500)
Star class	0.309	0.336
	(0.462)	(0.472)
Top 25% in the competitive exams	0.205	0.233
	(0.404)	(0.423)
Top 10% in the competitive exams	0.087	0.105
	(0.282)	(0.307)
Observations	40,547	22,075

Notes: The table refers to the population of students who took their high school exit exams in science between 2010 and 2014 (column 1), or to the subsample of students whose high school was located in a local district with tracked or untracked prep schools offering a Math or Engineering major (column 2). The bottom part of the table (last four rows) further restrict each sample to the students who attended a prep school and persisted until the second year in the Math or Engineering major. For each sample of students, the table describes their baseline characteristics, namely their middle school and high school graduation results (rows 1 to 3), their age (row 4), their gender (row 5), and their low-income status (row 6). The table further displays students' post-high school trajectories, that is whether they enrolled in prep school and persisted until the second year in the Math or Engineering major (row 7), whether they attended a tracked school during their first year of prep school (row 8), if they entered a star class (row 9), and their performance during the Mines-Ponts competitive examinations (rows 10 and 11).

Table A3: Balancing tests: continuity of student baseline characteristics

	Coeff.	Mean below the median class rank	N
High school grad. with high honors	-0.006	0.872	193
	(0.095)		
End-of-high school av. exam score	0.045	1.642	193
	(0.120)		
End-of-high school math exam score	-0.087	1.638	193
	(0.087)		
Age < 18 at entry	-0.072	0.298	193
	(0.143)		
Girls	0.119	0.213	193
	(0.130)		
Low-income students	0.018	0.191	193
	(0.106)		
Boarders	-0.049	0.213	193
	(0.120)		

Notes: The table refers to the same sample of students as Figure 2 and shows the estimated impact of falling just above the median class rank on students' baseline characteristics (high school graduation results, age, gender, low-income, and boarding status). Standard errors are in parentheses, and all regressions include controls selected by the double lasso approach among student high school graduation results, first-year results, age, gender, low-income status, boarding status (excluding the dependent variable); a full set of class#year dummies; and a first-order spline function of the running variable. The second column shows the mean of each dependent variable for students whose first-year final ranking fell just below the median rank of their class (within –9 to –1 seats), and the third column shows the number of observations. The table shows that there is no discontinuity in student baseline characteristics around the median class rank.
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table A4: Robustness to the choice of control variables and functional forms

	Star class		Tier 1 *GE* program		Top 10% in the competitive exams	
Panel A: Robustness to control variables						
	No controls	All controls	No controls	All controls	No controls	All controls
1^{st} year rank > median class rank	0.526***	0.536***	0.372***	0.331**	0.275**	0.248*
	(0.080)	(0.082)	(0.127)	(0.128)	(0.137)	(0.141)
Observations	193	193	193	193	193	193
Panel B: Robustness to functional forms						
	Optimal poly.	Local linear	Optimal poly.	Local linear	Optimal poly.	Local linear
1^{st} year rank > median class rank	0.289**	0.526***	0.372***	0.372***	0.275**	0.275**
	(0.142)	(0.110)	(0.127)	(0.125)	(0.137)	(0.134)
Degree of opt. poly.	2		1		1	
Observations	193	193	193	193	193	193

Notes: Same working sample as in Table 1 and Table 2. Each column corresponds to a specific dependent variable, namely admission to a star class (columns 1 and 2), a dummy indicating admission to a Tier 1 *GE* program (columns 3 and 4), and a dummy indicating whether students scored within the top 10% of the Mines-Ponts competition (columns 5 and 6). For each dependent variable, the first row presents a similar analysis as in Table 1 and Table 2 with different sets of control variables, namely without any control variable for students' baseline characteristics (columns 1, 3, and 5), or with control variables for all available students' baseline characteristics (columns 2, 4, and 6). The second row shows similar results to the analysis in Table 1 and Table 2 with alternative functional forms, that is, columns 1, 3, and 5 report the results of falling above the median class rank using a polynomial function of the running variable whose optimal order is obtained by a bins test, and columns 2, 4, and 6 report the results using local linear estimations. Standard errors are in parentheses.
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table A5: Star class and exam performance: treatment effect derivatives

	Tier 1 *GE* program	Top 10% in the competitive exams
Treatment effect derivative (TED)	-0.002	0.017
	(0.012)	(0.013)
Observations	193	193

Notes: The table refers to the same sample of students as Figure 2. For each performance measure specified at the top of the column, the table reports the estimated treatment effect derivative following Dong and Lewbel (2015). Standard errors are in parentheses, and all regressions include controls selected by the double lasso approach among student high school graduation results, first-year results, age, gender, low-income status, boarding status; and a full set of class#year dummies.
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table A6: Balancing tests

	Outcomes				
	Middle school GPA	High school average grade	Age	Girls	Low-income students
Panel A: full sample of students whose high school is near a prep school					
High school in a district with a tracked prep school	-0.023	0.010	0.006	-0.004	-0.022**
	(0.021)	(0.017)	(0.008)	(0.004)	(0.011)
Mean dep. var.	0.978	0.133	17.134	0.454	0.114
N	362205	362205	362205	362205	362205
Panel B: subsample of students who persist to the 2^{nd} year of prep school					
High school in a district with a tracked prep school	-0.040	-0.007	-0.011	-0.002	-0.016
	(0.026)	(0.020)	(0.010)	(0.008)	(0.013)
Mean dep. var.	1.309	1.036	16.826	0.211	0.097
N	22075	22075	22075	22075	22075

Notes: The table refers to the sample of students who took their high school exit exams in science between 2010 and 2014, and whose high school was located in a local district with tracked or untracked prep schools offering a Math or Engineering major. Panel B is further restricted to the students who attended a prep school and persisted until the second year in the Math or Engineering major. Each column corresponds to a specific regression, and reports the estimated impact of spending the high school senior year in a local district with tracked prep schools rather than in a local district with only untracked prep schools on the dependent variable mentioned above. Each regression includes a full set of dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution and cohort fixed effects. For Panel B, students' rankings are defined within our working sample of students who enroll in prep school and persist until the second year in the Math or Engineering major. Standard errors clustered at the local district level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A7: Tracked prep schools, star classes, and exam performance — Robustness to the choice of control variables

	Outcomes				
	2^{nd} year of prep school	Tracked prep school	Star class	Top 25% competitive exams	Top 10% competitive exams
Without controlling for all available student characteristics					
High school in a district with a tracked prep school	-0.003	0.304***	0.162***	0.079***	0.045***
	(0.003)	(0.039)	(0.025)	(0.024)	(0.015)
Control variables selected by double lasso					
High school in a district with a tracked prep school	-0.003	0.308***	0.165***	0.080***	0.043***
	(0.003)	(0.041)	(0.027)	(0.027)	(0.016)
Mean dep. var.	0.061	0.661	0.336	0.233	0.105
N	362205	22075	22075	22075	22075

Notes: The table refers to the same samples of students as Table 4 and reproduces the same analysis with different control variables. Each regression of the top part only controls for a full set of dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution and cohort fixed effects. Each regression of the bottom part includes controls selected by the double lasso approach among students' middle school and end-of-high school average scores, age, gender, low-income status, dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution, and cohort fixed effects. For columns 2 to 4, students' rankings are defined within our working sample of students who enroll in prep school and persist until the second year in the Math or Engineering major. Standard errors clustered at the local district level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A8: Baseline ability, tracked prep schools, star classes, and exam performance — Robustness to the choice of control variables

	Outcomes				
	2^{nd} year of prep school	Tracked prep school	Star class	Top 25% competitive exams	Top 10% competitive exams
Without controlling for all available student characteristics					
High school in a district with a tracked prep school	-0.005**	0.342***	0.107***	0.021**	0.008**
	(0.002)	(0.047)	(0.020)	(0.011)	(0.003)
HS in a district with a tracked prep school#Medium baseline ability	0.005	-0.019	0.076***	0.071***	0.038***
	(0.007)	(0.025)	(0.026)	(0.023)	(0.013)
HS in a district with a tracked prep school#Top baseline ability	0.014	-0.101***	0.098***	0.110***	0.079***
	(0.012)	(0.035)	(0.035)	(0.029)	(0.030)
Control variables selected by double lasso					
High school in a district with a tracked prep school	-0.004**	0.343***	0.107***	0.022	0.008
	(0.002)	(0.048)	(0.021)	(0.014)	(0.005)
HS in a district with a tracked prep school#Medium baseline ability	0.004	-0.020	0.075***	0.069***	0.037***
	(0.007)	(0.024)	(0.025)	(0.021)	(0.011)
HS in a district with a tracked prep school#Top baseline ability	0.014	-0.099***	0.101***	0.112***	0.079***
	(0.012)	(0.035)	(0.034)	(0.027)	(0.028)
Mean dep. var.	0.061	0.661	0.336	0.233	0.105
N	362205	22075	22075	22075	22075

Notes: The table refers to the same samples of students as Table 4 and reproduces the same analysis with different control variables. Each regression of the top part only controls for a full set of dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution and cohort fixed effects. Each regression of the bottom part includes controls selected by the double lasso approach among students' middle school and end-of-high school average scores, age, gender, low-income status, dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution, and cohort fixed effects. For columns 2 to 4, students' rankings are defined within our working sample of students who enroll in prep school and persist until the second year in the Math or Engineering major. Standard errors clustered at the local district level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A9: Estimating the effects of tracked schools and of star classes on exam performance — An instrumental variable approach

	Outcomes	
	Top 25% competitive exams	Top 10% competitive exams
Tracked prep school	-0.218**	-0.175***
	(0.087)	(0.059)
Star class	0.887***	0.600***
	(0.158)	(0.144)
N	22075	22075

Notes: The table refers to the same samples of students as Table 4, columns (4) and (5). Each column corresponds to a specific dependent variable and shows the estimated effects of attending a tracked school and of attending a star class, when we instrument these independent variables by the interactions between a dummy variable indicating whether students' high school is located in a local district with tracked prep schools and three dummy variables indicating students' terciles in the distribution of high school math exam scores. Each regression includes a full set of dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution and cohort fixed effects, as well as additional controls for students baseline characteristics (middle school and end-of-high school average scores, age, gender and low-income status). The Cragg-Donald Wald F statistic for the first stage is equal to 42, which is well above the Stock-Yogo 10% critical value (13). Standard errors clustered at the local district level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A10: Baseline ability, tracked prep schools, star classes, repetition and peer characteristics

	Outcomes			
	Peer homogeneity (P10/P90)	P10 of second-year classmates	P90 of second-year classmates	Repetition of the 2^{nd} year
High school in a district with a tracked prep school	0.023***	1.921***	2.450**	0.015
	(0.007)	(0.501)	(1.003)	(0.022)
HS in a district with a tracked prep school#Medium baseline ability	0.028***	2.674***	0.940	-0.002
	(0.008)	(0.715)	(0.897)	(0.013)
HS in a district with a tracked prep school#Top baseline ability	0.045***	4.265***	-0.126	-0.015
	(0.011)	(0.990)	(1.025)	(0.018)
Mean dep. var.	0.255	20.356	72.018	0.254
N	22075	22075	22075	22075

Notes: The table refers to the same samples of students as Table 4 and uses the same specification. Each column corresponds to a specific regression and reports the estimated impact of spending the high school senior year in a local district with tracked prep schools rather than in a local district with only untracked prep schools on the dependent variable mentioned above. The analysis is augmented by interactions between the type of high school local districts and students' terciles in the distribution of high school math exam scores. Each regression includes a full set of dummy variables indicating the centile of students' position in the end-of-high school math exam score distribution and cohort fixed effects, as well as additional controls for students baseline characteristics (middle school and end-of-high school average scores, age, gender and low-income status). Students' rankings and their classmates' rankings are defined within the sample of students who enroll in prep school and persist until the second year in the Math or Engineering major. Standard errors clustered at the local district level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Table A11: Baseline ability, tracked prep schools, star classes, and exam performance — Robustness to the exclusion of Paris and the Paris region

	Outcomes				
	2^{nd} year of prep school	Tracked prep school	Star class	Top 25% competitive exams	Top 10% competitive exams
Baseline specification					
High school in a district with a tracked prep school	-0.004	0.298***	0.149***	0.061***	0.029***
	(0.003)	(0.039)	(0.026)	(0.014)	(0.009)
Adding interractions with students' baseline ability					
High school in a district with a tracked prep school	-0.005**	0.318***	0.101***	0.007	0.004
	(0.002)	(0.046)	(0.026)	(0.007)	(0.004)
HS in a district with a tracked prep school#Medium baseline ability	0.002	0.001	0.065**	0.055***	0.021**
	(0.005)	(0.029)	(0.025)	(0.017)	(0.008)
HS in a district with a tracked prep school#Top baseline ability	0.013	-0.064*	0.088**	0.116***	0.058***
	(0.013)	(0.037)	(0.034)	(0.023)	(0.019)
Mean dep. var.	0.055	0.617	0.306	0.192	0.081
N	282211	15617	15617	15617	15617

Notes: The table reproduces the same analysis as in Tables 4, while excluding from the sample Paris and its surrounding region (referred to as "Île-de-France"). Standard errors clustered at the local district level are in parentheses. * significant at 10%. ** significant at 5%. *** significant at 1%.

Appendix B

Competitive examinations

At the end of their second year of preparation, students take entrance exams for admission into *GE* graduate programs. There are more than two hundred such *GE* programs, but most coordinate themselves to recruit on the basis of common exams, thus limiting the number of test days for prep students. As a consequence, most students take only four national competitive examinations: the so called X-ENS competitive examination, which is used to recruit students for both the École Polytechnique (called X) and the four Écoles Normales Supérieures (located in Paris, Lyon, Rennes, and Saclay); the Mines-Ponts competitive examination (a group of 9 *GE* programs); the CentraleSupelec competitive examination (10 *GE* programs); and the Polytechnic common competitive examination (called CCP, about 60 *GE* programs). At the end of these exams, each competition produces a ranking, students produce a prioritized list of *GE* programs they wish to join, and the matching is done centrally, with the highest-ranked students given priority to join the *GE* program of their choice. At the end of their second year, the students who are unsatisfied with the *GE* programs they can enter have the option of repeating a year. On average, about a quarter of first-time second-year prep students in the Math or Engineering major repeat a year. The X-ENS competitive examination and, to a lesser degree, the Mines-Ponts and CentraleSupelec competitive examinations are the most prestigious and selective. Each year, about 8,300 students with a Math major (the MP/MP* group) take competitive entrance exams to enter scientific *GE* programs, and these programs offer a total of about 4,100 seats. However, only about half (2,000) are offered in the three most prestigious competitive examinations of X-ENS, Mines-Ponts, and CentraleSupelec.

The Mines-Ponts competitive examination

Our datasets provide us with information on the results of all prep students in the Mines-Ponts competition, regardless of whether they decide to enter one of the (9) programs who recruit through this competition. As mentioned above, this is one of the most prestigious and popular competitive examinations. It is taken by most prep students with a Math or Engineering major (more than 5,000 Math major applicants in 2014) and by nearly all students in prep school L.

This competition has also the advantage of producing a ranking on the same scale for a very large number of prep students (star and non-star together), whereas the X-ENS competitive examination is taken mainly by students from star classes, and the CentraleSupelec competitive examination produces many partial rankings because students are not obliged to apply jointly to all the *GE* programs of this competition (which is, on the other hand, the case for the Mines-Ponts competitive exam). Finally, top students from star classes usually do not take the CCP competitive exam.

Like the other competitions, the Mines-Ponts competition is organized in two steps: students take written exams first, with those scoring highest then taking oral exams. For each of the students, we know if they participated in the competition, if they managed to be eligible for the oral exams after the written exams (which generally means that they are in the top 25% to 30% of all candidates after the written tests) and, if so, we know their final ranking after the oral exams. We use as main indicators of success the fact of having finished in the top 25% or in the top 10% of this competition.

Tier 1 and Tier 2 programs

The data specifically available for prep school L allows to develop alternative measures of student performance. We have information on the specific *GE* program in which each student of this prep school ends up enrolling, and consequently we can measure for each of them whether they were successful in gaining admission to one of the (fourteen) programs considered to be Tier 1.

This small group of elite programs correspond to the *GE* programs recruiting through the X-ENS competitive examination, as well as the three most selective programs recruiting through the CentraleSupelec competitive examination, and the five most selective programs recruiting through the Mines-Ponts competitive examination.[16] In 2014, these Tier 1 programs admitted a little over 1,000 students from the MP/MP* prep program, that is between the top 10% and the top 15% of applicants with a math major.

For those who fail to enter a Tier 1 program, we will be able to identify whether they qualify for a program generally regarded as Tier 2. This group includes the 4 programs recruiting though the Mines-Ponts competitive examination and the 4 programs recruiting though the CentraleSupelec competitive examination that are ranked just after the Tier 1 programs in each of the two competitive examinations.[17] The number of seats offered in these Tier 2 programs corresponds to about 5% of applicants, so one needs to be in the top 15% to 20% to gain admission to at least one Tier 2 programs.

[16]The GE programs generally considered to be the most prestigious and which we qualify as Tier 1 are the following: *École Polytechnique*, the four *Écoles Normales Supérieures* (*Paris*, *Paris-Saclay*, *Lyon*, *Rennes*), *École Supérieure de Physique et de Chimie Industrielles*, *École Nationale Supérieure des Mines de Paris*, *École Nationale des Ponts et Chaussées*, *École Centrale Paris*, *École Supérieure d'Electricité*, *École Nationale Supérieure des Télécommunications*, *École Nationale Supérieure des Techniques Avancées*, *Institut Supérieur de l'Aéronautique et de l'Espace*, and *École Centrale Lyon*.

[17]Tier 2 programs are as follows: *Ecole Nationale de la Statistique et de l'Administration Economique*, *Ecole Nationale Supérieure des Mines de Nancy*, *Ecole Nationale Supérieure des Mines de Saint-Etienne*, *Ecole Nationale Supérieure des Télécommunications de Bretagne*, *Centrale Nantes*, *Centrale Lille*, *Centrale Marseille*, and *Institut d'Optique Graduate School*.