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ABSTRACT

Tracking When Ranking Matters*

This paper investigates the effect of grouping students by prior achievement into different classes (or schools) in settings where students are competing for admission to programs offering only a limited number of places. We first develop a model that identifies the conditions under which the practice of tracking students by prior achievement increases inequalities between students that do not initially have the same academic background, such as may exist between students with different social backgrounds. We then test our model using new data on the competitive entrance exams to elite scientific higher education programs in France. We find that 70% of the inequality in success in these exams between students from different social backgrounds can be explained by the practice of tracking students by prior achievement that prevails during the years of preparation for these exams.

JEL Classification: C13, C51, 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 can improve student performance, if only because it allows teachers to adapt their teaching better. However, the effects are not necessarily the same for all students, especially when those students assigned to lower tracks suffer from less ambitious instruction or less motivated peers. This may result in a significant increase in outcome inequality between initially weaker and stronger students.

This issue is particularly crucial when student success depends on relative and not absolute performance. This is the case, for example when students from different tracks are competing for a limited number of places in highly sought-after programs, and when only the best will be selected, sometimes following a national examination. In such settings, the overall effect of tracking on learning outcomes is of little relevance. If tracking equally improves the performance of initially stronger or weaker students, it will not impact their overall ranking, thereby leaving the profile of those eventually admitted to the best programs unaffected. 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 paper, we explore these issues in the context of undergraduate programs that prepare students for graduate programs offering only a limited number of seats. Such restrictions on the number of seats are implemented in many countries, both at the undergraduate and graduate level, usually for medical, law, and engineering studies. To understand better the impact of tracking in such settings, we first develop a model that suggests that tracking students by prior achievement contributes to increasing the access gap to top graduate programs if and only if (a) it has a relatively stronger impact on students admitted to the highest preparation track *and* (b) student exam performance depends in part on abilities that become relevant only after the assignment of students to the different preparation tracks. If the abilities that determine students' results at the end of their preparation are all revealed before student assignment, tracking may reinforce the performance gaps between initially stronger and weaker students, but it will not change students' final ranking, and thus will have no effect on the profile of students admitted to the most selective graduate programs.

The model further suggests that for conditions (a) and (b) to be met, it is sufficient that there is a discontinuous increase in the probability of access to the most selective graduate programs between the first students rejected and the last students admitted to the highest preparation track, with the probability of the first students rejected being positive and that of the last students admitted being less than one (otherwise, entire second-year classes obtain identical final results and it becomes impossible to exclude the possibility that everything is played out at the end of the first year). In such contexts, the stronger the discontinuity, the larger the effect of tracking on the profile of students admitted to top programs.

In a second step, we develop a regression discontinuity design to recover the relevant parameters of our model, using longitudinal data from an undergraduate program that prepares 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. Like many elite science programs around the world, these graduate programs suffer from a very significant deficit of students from modest backgrounds, even though they recruit through standardized national competitive examinations focusing solely on academic skills (see, e.g., Bonneau et al., 2021). The empirical question is to understand whether the two-year period of preparation for these competitive examinations, and particularly the tracking of students according to prior academic performance implemented at the end of the first year of preparation, contributes to aggravating or attenuating the underrepresentation of students from modest backgrounds in the most prestigious *GE* programs.

Our analysis generates several key results. First, consistent with the hypothesis that tracking affects final rankings, our regression discontinuity model reveals a very significant (but not zero to one) increase in the probability of access to top graduate programs between the first students admitted to the highest preparation track (so-called "star" class) and the last students not admitted to that track. Specifically, at the end of their preparation, the probability of being admitted to a first-tier graduate program is about 0.85 for the former against only 0.45 for the latter. Our data also show that low-income students are only about half as likely to enter a "star" class as high-income students, which reflects that they are initially less well prepared for the heavy demands (and workload) of prep programs.

Overall, the tracking of students contributes to generating very significant inequalities in access to top *GE* programs between low- and high-income students. According to our estimates, more than 70% of the access gap between these students is explained by the fact that low-income students enter the highest track less often than their high-income peers. Additional analysis of exhaustive administrative data covering all undergraduate prep programs suggests that our results have a scope that goes far beyond the prep program studied in this paper in that in other prep programs students from modest backgrounds are also less likely to enter star classes. This is ultimately the main reason why they end up being even more underrepresented in top *GE* programs than they already are in prep programs.

Our paper contributes to the longstanding debate on the impact of tracking by prior academic level (see Betts, 2011), recently renewed using experimental and quasi-experimental approaches (Card and Giuliano, 2016; Duflo, Dupas and Kremer, 2011; Wu et al., 2019). In the context of programs preparing for competitive entrance exams, tracking significantly accentuates performance inequalities between students initially best and least prepared for elite higher education, with the indirect consequence of reinforcing socioeconomic gaps in access to elite graduate programs. These results are in sharp contrast to those obtained by Duflo, Dupas and Kremer (2011) in elementary schools in Kenya, where tracking equally benefits the 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. The variability of diagnoses is suggestive that the impact of tracking depends on student age, what is at stake, and on the cultural context.

Our paper also contributes to the debate about the lack of diversity within elite university programs, and about the reasons why high achievers from modest backgrounds fail to join the best institutions of higher education. Existing work highlights the lack of information that high achievers from modest backgrounds suffer from, particularly in terms of the financial aid they can receive or in terms of the prospects that joining the most selective tracks of higher education would open up (Dynarski et al., 2021; Hoxby and Avery, 2013; Hoxby and Turner, 2015). Many tutoring initiatives aimed at high school students from modest backgrounds have emerged, even if existing evaluations are not necessarily very encouraging (Ly, Maurin and Riegert, 2020). When access to elite institutions is regulated by a standardized national competitive examination, our work highlights the important role played by how the preparation for this examination is organized.

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. In countries where selection principles are vaguer and less standardized, such as entrance to the most prestigious US universities, the lack of transparency of procedures feeds recurring accusations of discrimination.[1] 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; Bourdieu and Passeron, 1977). 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 long and arduous preparation, the organization

[1]On Harvard University's charge that it discriminates against Asian- and African-American applicants, see Arcidiacono, Kinsler and Ransom (2019, 2022). On the mechanisms of discrimination against Jewish students at entrance to elite universities in interwar America, see Karabel (2005).

of which, often spread across many institutions and classes of extremely variable academic level, can exacerbate rather than smooth any prevailing inequalities. As far back as Ancient China, success in competitive examinations came to be the preserve of just a few hundred families, being the only ones able to both influence the content of tests and prepare their children for these tests (Clark, 2015; Elman, 2000, 2013).

The structure of this paper is as follows. Section 2 develops our conceptual framework, Section 3 describes the institutional framework, and Section 4 presents the data. Section 5 provides the results from our regression discontinuity approach. Section 6 discusses the external validity of our main empirical results and the potential underlying mechanisms. Finally, Section 7 concludes the paper.

2 Conceptual Framework

Let us consider a two-year prep program (denoted L) that recruits high school science graduates with the objective of preparing them for competitive entrance exams that determine student access to scientific *GE* graduate programs. There are two first-year classes of about 50 students each, to which freshmen are randomly assigned. At the end of the first year, students are ranked within their class according to the results obtained throughout the year, and we assume that the program manager has the choice of either tracking students according to their first-year ranking into two second-year classes (star vs non-star), or of randomly constituting two homogeneous second-year classes. In this section, we develop a conceptual framework to understand what is at stake in this choice, and to measure its impact on the inequalities in exam success (if any) at the end of the second year.

2.1 The model

For each student i, we denote r_i as the proportion of first-year classmates that performed worse in the first year. This variable is uniformly distributed on $[0, 1]$ and captures the rank of student i in that class at the end of the first year. It likely depends depends on each student's family background and on the preparation they received during high school, that is, prior to entering the prep program. When the prep program manager opts for tracking second-year students into a star and a non-star class, access to the star class (noted $T_i = 1$) is reserved for students ranked in the upper half of their first-year class, namely,

$$T_i = 1 \text{ if and only if } r_i > \frac{1}{2}.$$

Tracking students into a star and a non-star class according to their first-year class rank may affect all students whether they are in the top or bottom half of their first-year class, but the effect is not necessarily the same on those students accessing the star class. If we denote Y_i as the performance of student i at the end of the second year, we assume the following linear model,

$$Y_i = a_0 + a_1 N_i + b N_i \times T_i + c r_i + v_i,$$

where N_i is a variable indicating whether the program manager opts for tracking. Parameter a_1 captures the impact of tracking on students whose first-year rankings are in the bottom half of the distribution, parameter b captures the differential impact of tracking on top-half first-year students, and parameter c captures how the academic level achieved at the end of the first year affects performance at the end of the second year, irrespective of whether there is tracking. For simplicity, we assume c is nonnegative.

If the program manager chooses to track students into star and non-star classes, parameter b can be identified using a simple regression discontinuity analysis around the $r = \frac{1}{2}$ threshold, as explained below. Finally, variable v_i is assumed to be independent of r_i. It captures the academic potential that is revealed only in the second year of preparation and that cannot be predicted by the first-year class ranks.

In this setting, the first-year program reviews and deepens concepts first studied in high school, whereas the second-year program deals with more difficult and novel concepts for which students were much less prepared in high school, even when they attended the best high schools. Anecdotal evidence suggests that a significant number of typical first-year students increasingly come into their own during the second year.

With these notations, admission to top *GE* programs at the end of the second year ($G_i = 1$) is written:

$$G_i = 1 \text{ if and only if } Y_i > s,$$

where s is an admission threshold determined each year so that $P(G_i = 1) = P_0$, where P_0 captures the *numerus clausus* constraint, that is the fact that the number of seats offered in top *GE* programs is fixed in advance and represents a fixed proportion (P_0) of applicants. For simplicity, we assume that P_0 is smaller than $1/2$.

Finally, we denote P^+ (P^-) as the probability that a student ranked in the top (bottom) half of a first-year class ends up being admitted to a top *GE* program at the end of the second year. We have,

$$P^+ = P\left(Y_i > s \mid r_i > \frac{1}{2}\right) \text{ and } P^- = P\left(Y_i > s \mid r_i \leq \frac{1}{2}\right),$$

and (using the fact that $P\left(r \leq \frac{1}{2}\right) = \frac{1}{2}$) the *numerus clausus* constraint can be rewritten $P^{+}+P^{-} = 2P_0$.

The inequalities in access to top *GE* programs between top- and bottom-half students are captured by $I = P^{+} - P^{-}$ and the first basic question is to identify the impact of tracking on I.

2.2 Tracking and inequalities when v or b are negligible

In our setup, the first important result is that the impact of tracking on $I = P^{+} - P^{-}$ does not depend on the overall effect of tracking on student performance, as captured by parameter a_1. It depends only on whether tracking has a differential impact on top- and bottom-half students (i.e., parameter b) as well as on the importance of v, namely the academic potential that only becomes apparent in the second year when teachers address the newest and most challenging topics.

Specifically, when b is negligible, tracking may change the bar for admission to top programs, but it has no effect on the final ranking of students nor on inequalities. When v is negligible, tracking can reduce inequalities if b is negative by helping the best students in non-star classes to pass ahead of the weakest students in star classes. But if b is positive, tracking only strengthens the advantages of the highest-ranked students and does not change the profile of students admitted to top programs. To sum up, we have,

Proposition 1 (inequalities when b or v are negligible): When b is negligible, tracking has no effect on inequality in access to top GE programs, irrespective of whether it contributes to increasing the overall academic level of students. Similarly, when v is negligible (zero variance) and b is positive, tracking has no effect on inequalities in access to top GE programs. When v is negligible and b is negative, tracking either has no effect on inequalities or helps to reduce them.

[Proof: see Appendix A].

Hence, one important first challenge is to test whether parameter b or variable v are negligible. This can be done by comparing the final outcomes of students just above and below the cutoff for admission to star classes. Specifically, when there is tracking at the end of the first year, the probability of gaining access to top *GE* programs at the end of the second year can be written:

$$P\left(G_i = 1 \mid r_i = \frac{1}{2}^{+}\right) = P\left(v_i > S - b - \frac{c}{2}\right) = 1 - F_v\left(S - b - \frac{c}{2}\right)$$

for students just above the first-year cutoff, and:

$$P\left(G_i = 1 \mid r_i = \frac{1}{2}^{-}\right) = P\left(v_i > S - \frac{c}{2}\right) = 1 - F_v\left(S - \frac{c}{2}\right)$$

for students just below the cutoff, with $S = s - a_0 - a_1$ and where F_v represents the cumulative distribution function of variable v. The difference between the two probabilities can be written as,

$$D = P\left(G_i = 1 \mid r_i = \frac{1}{2}^+\right) - P\left(G_i = 1 \mid r_i = \frac{1}{2}^-\right) = F_v\left(S - \frac{c}{2}\right) - F_v\left(S - b - \frac{c}{2}\right).$$

Consequently, insofar as we observe a significant discontinuity $D > 0$ at the threshold, this means that b is positive and that access to a star class is indeed associated with a higher success rate in competitive examinations. If in addition the probability of admission to top *GE* programs for students below the star class threshold is positive (i.e., $P\left(G_i = 1 \mid r_i = \frac{1}{2}^-\right) > 0$) and the probability of admission above the threshold is less than one (i.e., $P\left(G_i = 1 \mid r_i = \frac{1}{2}^+\right) < 1$), we have $v_{max} > S - \frac{c}{2}$ and $v_{min} \leq S - b - \frac{c}{2}$ (where $[v_{max}, v_{min}]$ represents the support of v) and therefore $v_{max} - v_{min} \geq b$: the discontinuity observed at the threshold also gives a minorant for the size of the support of variable v. The larger the discontinuity, the wider the support of v because the support of v contains the $\left[S - b - \frac{c}{2}, S - \frac{c}{2}\right]$ interval, where $S = s - a_0 - a_1$.

Proposition 2 (discontinuity): if we observe a discontinuous increase in admission to top *GE* programs at the $r = \frac{1}{2}$ cutoff, with $P\left(G = 1 \mid r = \frac{1}{2}^-\right) > 0$ and $P\left(G = 1 \mid r = \frac{1}{2}^+\right) < 1$, then b is positive and v is not negligible.

In essence, if $P\left(G = 1 \mid r = \frac{1}{2}^-\right) = 0$ and/or if $P\left(G = 1 \mid r = \frac{1}{2}^+\right) = 1$, it implies that entire second-year classes have identical final results and it becomes impossible to preclude that the support of v is negligible and that everything is played out at the end of the first year, even before the students are assigned to the different tracks. In the empirical part of the paper, we develop a regression discontinuity analysis that aligns with the assumption that b is positive and that v has a large support. This is the case on which we will now focus.

2.3 Tracking and inequalities when b is positive and v is nonnegligible

In this last subsection, we assume that b is positive and v is nonnegligible. We show that in this case, tracking increases inequality and that the effect of tracking on inequality is even more sizable as b is large.

When b is positive and v is nonnegligible, the choice of tracking implies:

$$P^+ = P\left(v_i > S - b - cr_i \mid r_i > \frac{1}{2}\right) = 1 - \frac{2}{c}\int_{S-b-c}^{S-b-\frac{c}{2}} F_v(t)\, dt, \text{ and}$$

$$P^- = P\left(v_i > S - cr \mid r_i \leq \frac{1}{2}\right) = 1 - \frac{2}{c}\int_{S-\frac{c}{2}}^{S} F_v\left(t\right)dt,$$

where $S = s - a_0 - a_1$. The *numerus clausus* constraint can then be written,

$$\frac{1}{c}\left(\int_{S-b-c}^{S-b-\frac{c}{2}} F_v\left(t\right)dt + \int_{S-\frac{c}{2}}^{S} F_v\left(t\right)dt\right) = 1 - P_0$$

This constraint implicitly defines S as a function of b and c, namely $S = S\left(b, c\right)$. In Appendix A, we show that the partial derivative $S_b^{'}$ is in $\left(0, 1\right)$. By contrast, if there is no tracking, we can check that the same *numerus clausus* constraint can be written,

$$\frac{1}{c}\left(\int_{S_0-c}^{S_0-\frac{c}{2}} F_v\left(t\right)dt + \int_{S_0-\frac{c}{2}}^{S_0} F_v\left(t\right)dt\right) = 1 - P_0$$

where $S_0 = s - a_0$. This implicitly defines S_0 as a function of c, namely $S_0 = S_0\left(c\right)$, with $S_0\left(c\right) = S\left(0, c\right)$.

When there is tracking, the inequality index $I = P^+ - P^-$ is written:

$$I = P^+ - P^- = 2P_0 - 2P^- = 2P_0 - 2 + \frac{4}{c}\int_{S(b,c)-\frac{c}{2}}^{S(b,c)} F_v\left(t\right)dt.$$

Because $S = S\left(b, c\right)$ increases with b and $F_v\left(t\right)$ increases with t, it is easy to confirm that I itself increases with b. By taking the derivative of I with respect to b, we obtain $I_b^{'} = \frac{4}{c}S_b^{'}\left(F_v\left(S\right) - F_v\left(S - \frac{c}{2}\right)\right) > 0$.

When there is no tracking, the same inequality index is written:

$$I_0 = 2P_0 - 2 + \frac{4}{c}\int_{S_0-\frac{c}{2}}^{S_0} F_v\left(t\right)dt.$$

Given $S_0 = S\left(0, c\right)$, the level of inequality I_0 observed when there is no tracking corresponds to the level that can be observed when there is tracking and $b = 0$. When b is positive and v is nonnegligible, tracking contributes to increasing the index I compared with what it would be (I_0) in the absence of tracking. Furthermore, the $I - I_0$ impact is independent of the overall effect of tracking on student performance (as captured by a_1) but is even more important when b is large.

Proposition 3 (inequalities when b is positive and v is nonnegligible): When b is positive and v nonnegligible, tracking widens inequalities, and the magnitude $I - I_0$ of its impact on inequalities increases with b.

To summarize, our conceptual framework shows that tracking contributes to increasing inequalities in competitive exam results if and only if (a) its differential impact b on top-half students is positive and (b) student exam results depend at least in part on aptitudes v that are revealed only after their assignment to star and non-star classes. In this setup, a sufficient condition for tracking to affect inequalities in access to top programs is that there is a discontinuous increase in the likelihood of access to these programs between the first students rejected and the last students admitted to star classes, with the probability of the first students rejected being positive and that of the first students admitted being less than one. The magnitude of the impact of tracking on access gaps to top programs is then directly related to that of the discontinuity.

In the next section, we examine whether there exists a discontinuity in student performances around the threshold determining selection into the best and weakest classes to assess the effect of tracking on inequalities in the context of the undergraduate programs that prepare students for the competitive entrance exams to the French *Grandes Écoles*.

3 Institutional Context

The undergraduate programs preparing for the entrance exams of scientific *GE* programs 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). After two years of preparation, these 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 students is to be ranked in the top-15% so that they can enter one of the *GE* programs (among the dozen) that have been feeding the French scientific and economic elite for more than two centuries. In economics, for example, the four French Nobel Prize winners and the ten former French presidents of the Econometric Society are all alumni of one of the two most prestigious *GE* programs, namely the *École Polytechnique* or the *École Normale Supérieure* (*ENS, Paris*). In addition, the vast majority of executive committee members of the 40 largest French companies (i.e., the CAC40) are graduates of prestigious *GE* programs (Dudouet and Joly, 2010).

3.1 Preparatory programs

The prerequisite for success in *GE* competitive entrance exams is to be admitted to a science prep program following high school. There are about 400 such prep programs in France (called *Classes Préparatoires* *aux Grandes Écoles*, *CPGE*), whose selectivity and prestige are almost as variable as those of the *GE* programs themselves. At the top, there are a handful of ultra-selective and high-performing prep institutions in Paris and the surrounding region (*Lycées Louis Le Grand, Henri IV, Sainte-Geneviève, Stanislas, Hoche*...). At the bottom, a constellation of smaller, less selective prep programs located in towns of intermediate size, such as Auxerre, Brest, or Tarbes. At the top and bottom of the hierarchy, the prep program curriculum is identical and very heavy. The aim is to assimilate in two years several disciplinary programs (in math, physics, engineering sciences, computer sciences), each of which would ordinarily be taught in three years at university. Prep programs are known (and feared) for their heavy workload and the sacrifices required. The vast majority (85%) are public, and tuition fees are almost nonexistent. In addition, most prep programs offer boarding places at unbeatable rates. The prep program studied in this article is one of the most prestigious of these.

The first year of preparation (called *mathématiques supérieures* or *math sup*) cannot be repeated and remains relatively generalist, even if a distinction can be made between MPSI-type classes (mainly math/physics, about 8,000 students each year), PCSI-type classes (physics/chemistry, about 8,000 students), PTSI classes (technology/engineering sciences, 3,000 students), and BCPST classes (biology/chemistry, 3,000 students) classes. The second year (called *mathématiques spéciales* or *math spé*) allows students to refine their specialization, and above all, generate a new selection process: whether they choose to focus on math (MP classes), physics (PC classes) or engineering sciences (PSI classes), the best students join “star" classes whereas the others have to make do with “non-star” classes. For example, the best students of MPSI classes join either an MP* class or (more rarely) a PSI* class, whereas their MPSI classmates join either an MP class or a PSI class. On average, about one-third of first-year students join a star class in the second year, but this can be as much as 50% in the most selective and prestigious prep programs (such as the one considered here).

In a given prep program, the numbers of first- and second-year classes are fixed along with the number of star classes, so that the proportion of first-year students joining star classes varies very little from one year to the next. The curricula used for star and non-star classes are similar and the teachers have similarly very strong qualifications.[2] In addition, students in both star and non-star classes prepare for the same competitive exams, especially in the most selective prep programs, like the one examined

[2]Teachers in prep programs are recruited each year among high school teachers. To teach in a French high school, teachers must pass a competitive examination (called the CAPES or aggrégation), and those chosen to teach in prep classes are generally selected among the top-ranked of their discipline, with a preference given to those that have also completed a Ph.D. and have received the best evaluations during their first years of teaching in high school. Teachers in preparatory programs earn a higher salary than high school teachers for fewer teaching hours. There are approximately 6,000 teachers in preparatory classes, less than 1% of the total number of secondary school teachers. Many are former students of the *ENS*, i.e., they belonged to the academic elite and now represent, in many ways, the elite of their profession.

here. 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. Not all prep programs offer all choices of second-year programs, so some students change prep programs at the end of the first year.

The prep program studied in this paper has two first-year classes of the MPSI type, as well as two second-year classes, one of the MP type and one of the MP* type. At the end of their MPSI year, 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 program that is just as prestigious and selective (hereafter, prep program M). The other half join either the MP class or another non-star class located in other, less selective, prep institutions. Figure B1 plots the main trajectories followed by students admitted to an MPSI class in prep program L for the 2011–2012 to 2013–2014 school years. Our main research question is to determine whether access to one of the star classes offered to the best MPSI students is, in itself, a factor determining success in the *GE* competitive examinations.

3.2 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 (CCMP, a group of 9 *GE* programs); the CentraleSupelec competitive examination (10 *GE* programs); and the Polytechnic common competitive examination (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, students that are not happy with the *GE* programs they can enter have the option of repeating a year. In the prep program under consideration, between a quarter and a third of students 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. For the MP/MP* group of students, the different *GE* programs offer a total of about 4,500 seats each year, but only about one-third (1,500) are offered in the three most prestigious competitive examinations of X-ENS, Mines-Ponts, and CentraleSupelec.

4 Data and Variables

We have exhaustive information on students admitted to the two MPSI classes of prep program L between 2011–2012 and 2013–2014 (N = 255). For each student, we know their 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 have information on 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 to 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 that repeat a year, we know the *GE* program they enter at the end of their third year of preparation. Finally, we have detailed information on student rankings in the Mines-Ponts competitive entrance exam (at each participation), regardless of whether individual students decide to enter one of the nine *GE* programs recruiting through this exam. This competitive entrance examination is taken by most students in preparatory programs (more than 5,000 MP/MP* candidates in 2014) and by nearly all students in the prep program examined here.

Table B1 in Appendix B describes our working sample. This paints a typical picture of one of the most selective prep programs, with many very good students from wealthy backgrounds and very few girls. In evidence, in our sample 84% of students passed the 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 is in our sample is just 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).

4.1 Student performance

Given the available information, we can measure student performances in the *GE* competitive examinations in several ways. The first possibility is to use student rankings in the Mines-Ponts competitive examination.[3] As we have already pointed out, this is one of the most prestigious and most popular competitive examinations (5,500 candidates) and it is taken by almost all the students in prep program L (91%). This competition (like the others) is organized in two steps: students take written exams first, with those scoring highest then taking oral exams. For all students in our sample, we know if they are eligible to take the oral exams of the Mines-Ponts competition after the written exams (which means that they are among the top-30% of candidates) and, if so, we know their final ranking after the oral exams. For a prep program as selective as ours, an indicator of success in this competition is to finish in the top-10% of candidates.

Another approach is to rely on the hierarchies of prestige of *GE* programs used each year by most prep programs to present their own results, or by the press to compare the performance of the different prep programs (and to rank these programs). Each year, the specialized magazine *L'Étudiant* publishes a ranking of prep programs which is a reference and whose central criterion is the proportion of students admitted to one of the following 12 schools: *École Polytechnique*, the four *Écoles Normales Supérieures* (*ENS Paris*, *ENS Paris-Saclay*, *ENS Lyon*, *ENS Rennes*), *École Nationale Supérieure des Mines de Paris*, *École Nationale des Ponts et Chaussées*, *École Centrale Paris*, *École Supérieure d'Electricité*,[4] *École Nationale Supérieure des Télécommunications*, *École Nationale Supérieure des Techniques Avancées*, *Institut Supérieur de l'Aéronautique et de l'Espace*, and *École Centrale Lyon*. This small group of programs includes 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.[5] In the remainder of the paper, we refer to programs in this group as Tier-1 programs, and one criterion for performance in the competitive exams will be to succeed in entering a Tier-1 program. In 2014, these Tier-1 programs admitted a little over 1,000 students from the MP/MP* prep program, that is the top-15% of applicants.

A last approach is to infer the final overall rank of students from knowledge of the *GE* program they enter and using information on the sizes and ranks of all *GE* programs. The hierarchy of prestige and selectivity of the *GE* programs (especially at the top of the hierarchy) is agreed upon, even if there is no official detailed hierarchy.[6] At the top, *École Polytechnique* and *ENS Paris* stand out. In 2014, these

[3] The X-ENS competitive examination is taken mainly by students from star classes, whereas the CentraleSupelec competitive examination produces many partial rankings because students are not obliged to apply jointly to all the *GE* programs (which is, on the other hand, the case for the Mines-Ponts competitive exam). Finally, top students from star classes do not take the CCP competitive exam.

[4] In 2015 *École Centrale Paris* and *École Supérieure d'Electricité* merged and became *École CentraleSupelec*.

[5] We also add to this list of top *GE* programs the *École Supérieure de Physique et de Chimie Industrielles* (*ESPCI*) which also recruits through the X-ENS competitive exam, and which recruited just one student from our sample.

[6] By consulting the websites of the different prep programs, we can confirm that all use more or less the same classification

admitted a total of 233 MP/MP* students, which corresponds to about 3.1% of all MP/MP* applicants. Hence, to join one of these two *GE* programs, students must finish on average among the top-1.5% of applicants. Next come the most selective schools in the Mines-Ponts competitive examination (i.e., Mines de Paris and Ponts et Chaussées, a total of 100 MP/MP* students in 2014), to which we can add the most selective school in the CentraleSupelec competitive examination (École Centrale Paris, 182 students) and the *École Normale Supérieure de Lyon* (41 students). The total number of students admitted to this second group of *GE* programs in 2014 was 323, which is about 4.3% of all applicants. Students joining these programs lie between the 3.1 and 7.4 percentiles of the distribution of applicants and therefore average around the 5.2 percentile. In other words, students entering these *GE* programs are on average in the top-5.2% of all prep students. Following the same methodology, we gradually construct a scale showing the average rank (expressed in percentile) of students entering each *GE* program. This scale is given in Table B2 in Appendix B.

5 A Regression Discontinuity Design

At the end of their first year of preparation, about half of the prep students under consideration are admitted to a star class. Our first objective is to test whether this in itself is a factor in exam success.

5.1 Graphical analysis

Student admission to a star class at the end of the first year of preparation 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.

Figure 1 depicts the variations in the probability of being admitted to a star class according to our measure of class rank, the median rank serving as the origin of the horizontal axis. The figure confirms that this probability is very low for students ranked below the median and very high for students ranked above the median. The likelihood of admission also 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.

In the following, our main working assumption is that admission to a star class is the only determinant of exam performance that varies discontinuously at the median. In other words, our working assumption is that the other potential determinants of exam performance are distributed continuously at the median.

to describe their results.

Given this assumption, discontinuities in exam performance at the median can be understood as a direct consequence of discontinuities in star class attendance. To test this assumption, Figures B3a to B3d in Appendix B compare student baseline characteristics (average end-of-high school exam score, math score at end-of-high school exams, gender, eligibility for means-tested financial aid) for students whose class rank is either just above or just below the median, using the same sample of students as Figure 1. Comfortingly, we do not discern any discontinuities, which is consistent with our working assumption.[7]

In this context, the question becomes whether the average performance of students in the competitive examinations taken at the end of their preparation 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 increase, 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 2 illustrates the quality of the *GE* programs into which students are admitted at the end of their preparation (as measured by the score described in Table B2) as a function of their first-year class rank, using the same sample of students as in Figure 1. In other words, Figure 2 shows our measure of a student's final overall ranking in the national competitive exams as a function of their class rank at the end of their first year of preparation. The figure shows a clear discontinuity between the final ranking of students below the median at the end of the first year of preparation and students above the median at the same point in the distribution where access to a star class varies discontinuously. Students below the median are admitted to *GE* programs that place them at around the 25$^{\text{th}}$ percentile of the overall ranking, whereas students above the median are admitted to *GE* programs that place them at around the 10$^{\text{th}}$ percentile (i.e., an average gap of 15 percentiles, equivalent to more than 1,100 ranks in the hierarchy of prep students).

Using the same sample as in Figures 1 and 2, Figure 3 plots the variations in the probability of joining a Tier-1 program as a function of first-year class rank. As explained above, Tier-1 programs include the *École Polytechnique*, the four *Écoles Normales Supérieures*, the *ESPCI*, as well as the three most selective *GE* programs in the CentraleSupelec competitive entrance examination and the five most selective *GE* programs in the Mines-Ponts competitive entrance examination; the number of seats offered in these programs corresponds to about 15% of the total number of applicants. 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. The prep program studied

[7] We also build on McCrary (2008) to test for possible manipulation of student rankings around the cutoff. Reassuringly, Figure B2 does not display any significant difference in (log) height at the cutoff.

in this paper 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 Appendix B, we provide additional graphical analysis of participation and success in the Mines-Ponts competitive examination, using the same sample and design as Figures 1 to 3 (see Figures B4 to B6). These figures do not show any discontinuities in the proportion of students registering for this competitive exam, nor is there a clear discontinuity in the proportion of students admitted to the oral exams after the written exams (although this proportion tends to be higher for those students above the median). By contrast, there is a very clear discontinuity in the proportion of students finishing in the top-10% of the CCMP competitive exam. This proportion remains below 20% for students below the median but jumps above 40% for students above the median.

In the conceptual framework developed above, the discontinuity revealed by Figure 3 (or by Figure B6 in Appendix B) suggests that neither the parameter measuring the impact of joining a star class (parameter b in the model) nor the variable measuring the academic potential that emerges in the second year of preparation (variable v) can be neglected (see Proposition 3). We are thus in the configuration where tracking very directly modifies the profile of students admitted to Tier-1 programs (see Proposition 4). When we analyze separately the group of students above and below the star class admission bar, we also observe that within each group, the probability of joining a Tier-1 program varies very little as a function of first-year class rank, suggesting that the c parameter in our model is close to zero. Differences in exam performance are large between students in star and non-star classes, but much smaller within each class, in line with the idea that the main source of inequality in exam success is the practice of tracking students into different classes at the end of the first year.

5.2 Regression results

In this section, we test the robustness of our graphical results by estimating a regression discontinuity model. Specifically, with variable r denoting the difference between each student's class rank and the median class rank at the end of the first year of preparation, we are going to 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.

In this analysis, the identifying assumption remains 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 B3 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.

Table 1 details the regression results when we employ the same sample as Figure 1 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 1, this analysis confirms that a student being ranked above the median of their class at the end of the first year (i.e., $r > 0$) very significantly increases (by about 50 percentage points) the probability of their 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 to 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 on the part of 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. Students just above the median gain access to *GE* programs recruiting on average 13 percentiles higher in the overall hierarchy of candidates. 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,[8] and a very significant decline in access to other, less prestigious, *GE* programs.

These results are in line with the idea that access to a star class is associated with a general increase in performance: students that are below the median and that would have been admitted to a Tier-3 program

[8]Tier-2 programs include the four least selective programs in the Mines-Ponts competitive entrance examination and the four programs ranked just below CentraleSupelec and Centrale Lyon in the CentraleSupelec competitive entrance examinations (namely, *Centrale Nantes*, *Centrale Lille*, *Centrale Marseille*, and *Institut d'Optique Graduate School*).

are admitted to a Tier-2 program when they are above the threshold, whereas students that would have been integrated into a Tier-2 program are admitted to a Tier-1 program. Table 2 also confirms that access to a star class increases very significantly the likelihood of entering the top-10% of the Mines-Ponts competition (+0.28**).

In Appendix Table B4, we show the regression results separately for low- and high-income students, and for male and female students. The discontinuity in access to star classes at the median tends to be stronger for low-income students than for high-income students, but the opposite is true for the discontinuities in performance, which are stronger for high-income students. These results are suggestive that access to a star class has an even stronger effect on the performance of high- than on low-income students. Similarly, the estimated discontinuity in access to a star class tends to be weaker for girls than for boys, but not the estimated discontinuity in performance, which is suggestive that the impact of access to a star class is stronger for girls than for boys. However, it should be emphasized that the small sample sizes make it impossible to reject the hypothesis of equality between the first stage and reduced-form effects estimated for the different subgroups.

Table 3 provides an estimation of the causal impact of access to a star class on student performance obtained by specifying $Z = \mathbb{1}(r > 0)$ as the instrumental variable. Consistent with the first stage and reduced-form estimates in Tables 1 and 2, Table 3 suggests that access to a star class 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, even though the differences between the two estimates are not statistically different from zero. The OLS estimate of the impact of star class access appears to provide a lower bound for the causal impact of star class access on student performance, a result we use in the following sections to explore the external validity of our diagnostics. Finally, Figure B7 and Table B5 show that our results are robust to alternative specifications for the regression discontinuity model.

5.3 Tracking and inequalities in access to top graduate programs

Tracking allows teachers to have more homogeneous classes and gives them the opportunity to adjust their teaching better to the actual academic level of their students. In the context of preparing for highly selective competitive exams, our results suggest that this practice benefits more students that adapt most quickly and achieve a ranking in the top half of their first-year class. Given this reality, the question arises as to whether students from all income groups have equal access to star classes, or whether access to star classes is unequal and constitutes an additional factor for inequality among children from different social backgrounds.

In most prep programs, student access to a star class is very much directly determined by their class rank at the end of the first year: if their rank is above a threshold set in advance (and linked to the number of star classes in the institution), access to a star class is almost guaranteed. By contrast, if their rank is below the threshold, access is almost impossible. In theory, therefore, tracking into star and non-star classes is a transparent and purely meritocratic mechanism. However, in practice, not all social groups are equally well equipped to face the shock of the very particular world of prep programs, with its incessant ranking (an assignment and a ranking every week) and its avalanche of work.

By way of illustration, the first three rows of Table 4 compare the end-of-first-year ranks of low- and high-income students[9] as well as their probability of entering a star class and their results in the end-of-high school examinations. These comparisons confirm that low-income students finish their first year of preparation significantly less highly ranked than high-income students and enter star classes significantly less often. More precisely, the class ranks of low-income students are on average 18 percentiles lower than those of their high-income classmates (i.e., 7 or 8 ranks lower in first-year classes of slightly less than 50 students) and have a 23 percentage point lower probability of accessing a star class (the probability is 0.27 for low-income students versus 0.51 for high-income students). These differences at the end of the first year of preparation are even more striking given that, just a year earlier, low-income students admitted to prep program L were just as exceptional as their high-income classmates. In particular, their results in the national end-of-high school examinations were as strong as those of their high-income peers, that is, about 1.6 standard deviations higher than those of other students. The difficulties experienced by low-income students during their first year of preparation translate into significantly poorer results in competitive exams than those of their high-income peers, as the last rows of the table prove. For example, their probability of entering the top-10% of the Mines-Ponts competition is 20 percentage points lower than that of high-income students (about 0.22 versus 0.42), whereas their probability of entering a Tier-1 program is 24 percentage points lower (about 0.46 versus 0.70).

Table 4 also details the performance gaps between low- and high-income students after controlling for the causal effect of accessing a star class, as estimated in the previous section. The adjusted gaps appear statistically insignificant at the conventional level and their estimated magnitude is about three times smaller than that of the unadjusted gaps. According to this analysis, if tracking were eliminated, the gap in access rates to Tier-1 programs would decrease by more than 70% (from 24 to 7 points).

It should also be noted that in this exercise, we assume that access to a star class has the same

[9] With our definition, recall that low-income students belong to the poorest 20% of prep students.

effect on low- and high-income students, whereas previous analyses suggest that the effect is stronger for high-income students, perhaps because their family environment better prepares them to take advantage of prep programs. If we were to take this heterogeneity into account, the contribution of star classes to the inequalities between low- and high-income students would be even stronger (we checked that it would then explain almost all of the observed gap). However, it must again be stressed that the small number of sample observations makes it impossible to estimate the heterogeneity of the effects precisely and this makes this type of exercise fragile.

It should also be emphasized that in this analysis, we implicitly assume that the effect of accessing a star class estimated for students ranked close to the median also holds for students ranked far from the median. Insofar as students benefit more from the instruction given in the classroom when they are among the best students in that class,[10] it can be assumed that the effect estimated by comparing the last students in star classes with the first in the non-star classes actually corresponds to an underestimation of the average differences in performance between the students in each class. Under this assumption, the approach developed in Table 4 again produces an underestimation of the effect of star classes on inequality.

6 External Validity and Mechanisms

6.1 External validity

So far, our analysis has used data from a single institution (prep program L) and we may then wonder whether our results have a more general significance. To shed light on this question, we rely on an exhaustive panel of administrative data describing access to star classes and performances in the Mines-Ponts competitive exams for all students admitted to MPSI-type prep programs between 2011–2012 and 2013–2014. These data do not provide information on the ranking of students at the end of their first year of preparation so it is not possible to use the regression discontinuity approach developed in the previous sections. However, it is possible to estimate the effect of accessing a star class on performances in the Mines-Ponts competition using a standard OLS approach, even if we have seen that it tends to underestimate the actual effect of accessing a star class. This analysis (available in Table B6) shows that access to a star class is associated with an average increase of more than 20 percentage points in the likelihood of finishing in the top-10% of the Mines-Ponts competition and with an increase of more than 40 percentage points when restricting the analysis to the top-10 performing prep programs, that is,

[10] This is confirmed, for example, by the results in Murphy and Weinhardt (2020) or Elsner and Isphording (2017).

orders of magnitude comparable to that obtained in the case of prep program L.

Based on these estimates, Table 5 proposes an evaluation of the impact of tracking on inequalities in access to the top-10% of the Mines-Ponts competition between low- and high-income students. To start, Panel A of Table 5 focuses on the 10 best-performing prep programs,[11] that is the closest prep programs to program L. The first three rows of the panel confirm that in these institutions as in prep program L, low-income students access star classes significantly less often than high-income students (their probability of accessing a star class is 8 percentage points lower than that of high-income students), and they obtain significantly poorer results in the competitive exams (with a probability of accessing the top-10% of the Mines-Ponts competitive exam of 0.34 against 0.43 for high-income students).[12] Finally, as in prep program L, this performance gap in competitive examinations appears to be explained in large part by a differential access to star classes. More precisely, once the effect of star classes on performance is neutralized, the adjusted performance gap between low- and high-income students is reduced by half. Panel B reproduces this analysis for all prep programs. The diagnosis is qualitatively similar: low-income students do significantly less well in competitive exams, but this is largely because they have a significantly lower access to star classes.

6.2 Mechanisms

The results obtained so far are suggestive that tracking is more beneficial for students that access the highest track and that this heterogeneity in the impact of tracking contributes to increased inequality in access to the best graduate programs between students with the highest and lowest initial academic backgrounds. In this final part of the paper, we discuss some of the mechanisms that may explain why tracking does not have the same effects on students accessing the lowest and highest tracks.

A first possible reason for the stronger boost in performances among students attending a star class compared with those attending a non-star class could be that only teachers in star classes prepare students for the most difficult Tier-1 competitive exams (X-ENS) whereas teachers in non-star classes would instead focus on the least difficult and prestigious exams (Centrale-Supelec and Mines-Ponts). In this context, one reason why students that barely made it into star classes end up with a higher probability of

[11] Taking as a measure of performance publicly available aggregate information on the proportion of students admitted in Tier-1 programs.

[12] The administrative data used for this analysis do not identify low-income students in the same way as the data we collected directly from prep program L. In the data we collected, the low-income student group only includes students that received means-tested financial aid, whereas the administrative data also includes students in the following income brackets that did not receive financial aid but were exempted from paying tuition fees (so-called "boursiers d'échelon zéro"). These differences in the definition of the low-income group explain why the estimates of the performance gap between the low- and high-income groups presented in Table 5 appear to be smaller than those presented in Table 4.

entering Tier-1 programs compared with those that barely failed to access these same classes could be driven by a higher probability of entering the *École Polytechnique* or the *ENS Paris* because students in non-star classes would simply not prepare for the entry exams of these specific programs. To test this potential mechanism, it is possible to study separately the effect of tracking on the probability of being admitted to the *École Polytechnique* or *ENS Paris*. Using the same sample as in Figures 1 and 3, Figure B8 depicts the variations in this probability as a function of first-year class rank. Figure B8 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 why tracking is more beneficial for initially stronger students.

A second explanation for the differential effects of tracking on students accessing star or non-star classes would be that the teachers in star classes are particularly efficient. As explained earlier, prep program teachers are civil servants recruited by the Ministry of Education from among secondary school teachers with the best results in the secondary school teacher recruitment competition and with the best evaluations in their first years of teaching in high school. Once recruited as prep teachers, they are assigned to a prep program where they typically teach a first-year class. Thereafter, they can only move from one position to another (i.e., from one prep program to another that is more prestigious or better located in their opinion) if positions become available, mostly as a result of retirement.[13] To move to another position (when one becomes available), teachers must apply, and the final decision is again made by central authorities, along with some input from prep program principals.

In this setting, the turnover of prep program teachers is very low, especially in the most prestigious programs, where teachers tend to arrive at the end of their careers and remain until retirement. For example, in prep program L, the math and physical science teachers in the star and non-star classes remained unchanged during our 3-year observation period and were all between 50 and 60 years of age. Over the 7-year period between 2007 and 2014, we found only a single replacement among the second-year mathematics and physical science teachers in prep program L, and that was linked to a retirement.

In the end, given their very low turnover and the high level of homogeneity in their initial recruitment, it seems quite unlikely that there are significant differences in pedagogical effectiveness between different prep program teachers, especially among those that have managed to be recruited as second-year teachers in one of the most prestigious prep programs, such as prep program L.

[13]They typically begin their careers teaching first-year classes in a lower-ranked prep program and then, through mobility, seek to be recruited as second-year teachers in more prestigious prep programs.

Another possible reason why initially stronger students would benefit more from tracking would be positive peer effects. If students benefit from being surrounded by better achieving peers, either because of direct assistance or indirectly through class emulation, then students that barely gain access to a star class would benefit from these higher-achieving peers, whereas students that just failed to rank above the class median would miss out on these positive externalities (see, e.g., Booij, Leuven and Oosterbeek, 2017).

A final explanation pertains to changes in the noncognitive abilities of students. It is possible that getting access to a star class boosts student confidence, or conversely, that failing to access such classes damages student motivation. These changes in student confidence or motivation could then impact their exam performance (see, e.g., Almlund et al., 2011). However, it should be remembered that according to our research discontinuity design estimates, access to star classes does not affect the probability of repeating a year after the first exam participation. Put differently, those students that fail to access star classes are just as capable of persevering to try to improve their final ranking, suggesting that their ambitions are not particularly diminished by being relegated to non-star classes.

7 Conclusion

In this paper, we first identify two conditions under which tracking students by prior achievement can influence their future success, in settings where that success depends on the relative rather than absolute level of performance. The first condition is that the practice of tracking students by prior achievement has a more positive effect on initially stronger students than on initially weaker students. The second condition is that student success depends at least in part on abilities that are revealed only after students are assigned to the different tracks, when teachers start to tackle newer concepts compared to what students have previously learned. We further show that for these two conditions to be met, it is sufficient that we observe a discontinuous increase in student success between the last students admitted to the most selective tracks, and the first students failing to gain admission to these tracks, with the probability of success being higher than zero in the lowest tracks and less than one in the highest tracks.

In a second step, we recover the relevant parameters of our model in the context of French undergraduate programs that prepare students to take competitive entrance exams for leading science graduate programs. This analysis focuses on three cohorts of students admitted into one of the oldest institutions where undergraduate students are prepared for these competitive entrance exams. Using a regression discontinuity design, we show that access to the most selective preparation tracks in this institution (so-called star classes) constitutes a decisive factor in exam success (although not zero to one). In other words, we find that in this context, tracking students by prior achievement during preparation years very significantly reinforces inequalities between initially weaker and stronger students, with the indirect consequence of reinforcing socioeconomic inequalities in exam success because low-income students are almost half as likely to enter the most selective preparation tracks compared with their higher-income counterparts. According to our estimates, in the absence of tracking, the socioeconomic access gap to top graduate programs could be reduced by 70%.

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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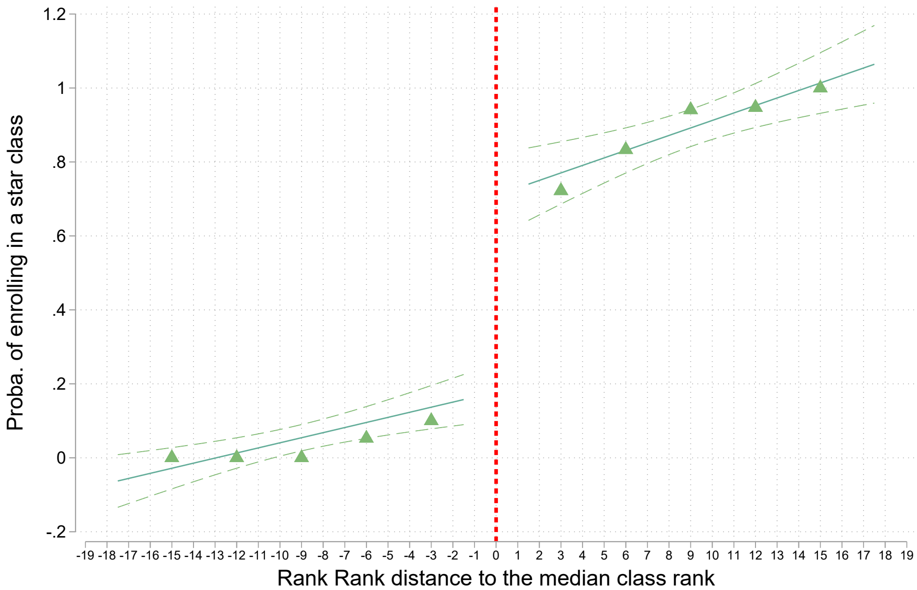


Figure 1: End-of-first-year ranking and admission to star classes

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 that 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).

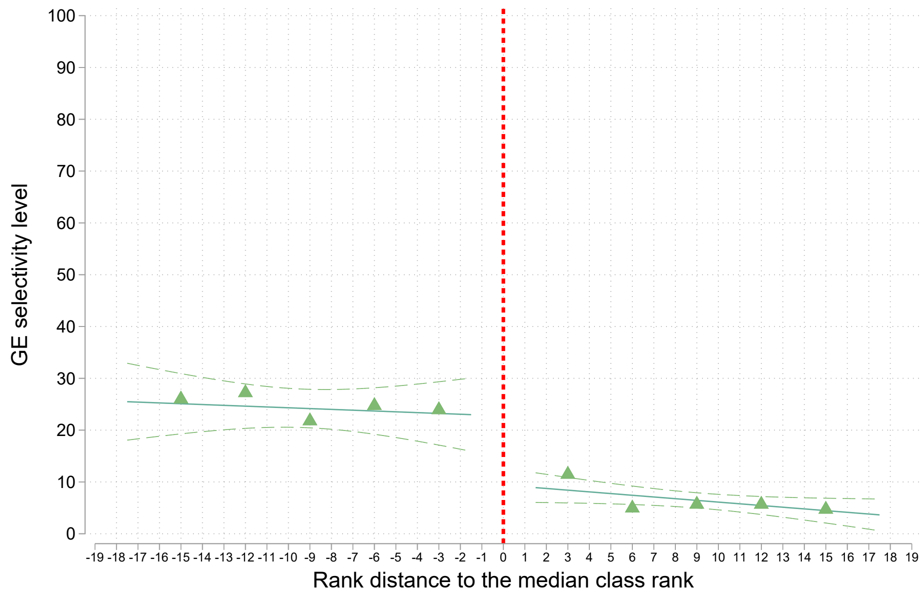


Figure 2: End-of-first-year ranking and *GE* selectivity level

Notes: The figure refers to the same sample as Figure 1, and shows the selectivity level of the *GE* programs into which students are admitted at the end of their preparation (as measured by the score described in Table B2), plotted against their final ranking at the end of the first year (with the median class rank as the origin). Below the median, students are admitted to *GE* programs recruiting on average among the top-25% of the overall ranking, whereas students above the median are admitted to *GE* programs recruiting on average among the top-10%.

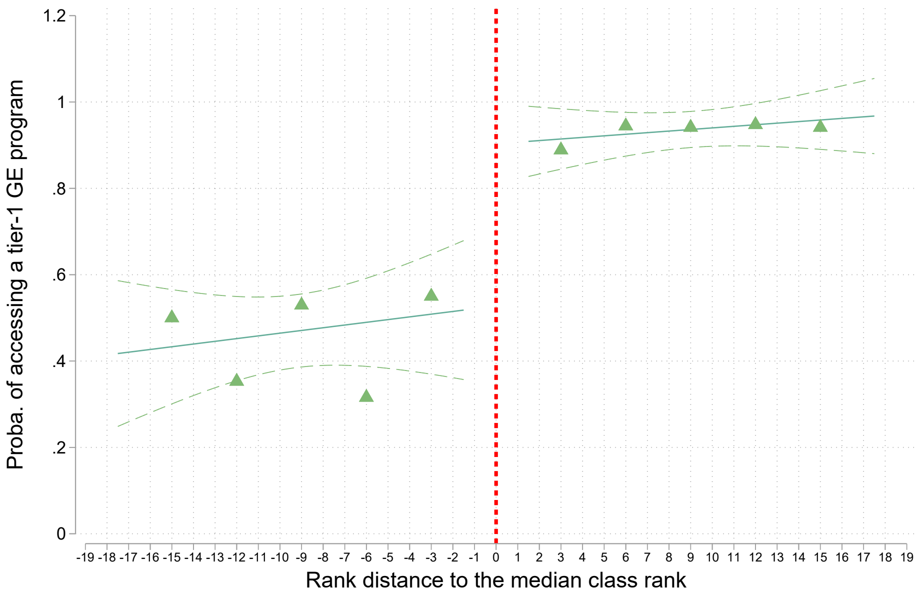


Figure 3: End-of-first-year ranking and admission into Tier-1 *GE* programs

Notes: The figure refers to the same sample as Figure 1, and shows the proportion of students admitted to a Tier-1 *GE* program ((*École Polytechnique*, the four *ENS*, *ESCPI*, *Centrale Paris*, *Supelec*, *Centrale Lyon*, and the five most selective schools of the CCMP 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.

Table 1: Discontinuities in schooling trajectories after the first year

	Coeff.	Mean below the median class rank	N
Type of track after the 1st year			
Star class	0.526***	0.106	193
	(0.078)		
-MP* (prep program L)	0.483***	0.000	193
	(0.085)		
-PSI* (prep program M)	0.044	0.106	193
	(0.082)		
MP (prep program L)	-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 1. Each row corresponds to a specific dependent variable, namely a dummy variable indicating admission to a star class 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 a non-star class in the MP track at other prep programs (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 from among student high school graduation results, first-year results, age, gender, low-income status, boarding status; a full set of cutoff 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: Discontinuities in competitive exam performance

	Coeff.	Mean below the median class rank	N
GE selectivity level	-13.316**	23.996	193
	(5.236)		
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)		
Eligibility to take CCMP oral exams	0.073	0.766	193
	(0.112)		
Top-10% in the CCMP compet.	0.275**	0.170	193
	(0.134)		

Notes: The table refers to the same sample of students as Figure 1. Each row corresponds to a specific dependent variable characterizing student performance during the competitive exams, namely, a variable indicating the selectivity level of the *GE* programs into which students are admitted at the end of their preparation as measured by the score described in Table B2 (row 1), a dummy indicating admission to a Tier-1 *GE* program (row 2), a dummy indicating admission to a Tier-2 *GE* program (row 3), a dummy indicating admission to a less prestigious *GE* program (row 4), a dummy indicating other types of studies (row 5), a dummy indicating eligibility to take the oral exams of the CCMP competition (row 6), and a dummy indicating whether students scored within the top-10% of the CCMP competition (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 selected among student high school graduation results, first-year results, age, gender, low-income status, boarding status; a full set of cutoff 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 CCMP 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
GE selectivity level	-25.299**	-21.701***
	(10.458)	(2.590)
Tier-1 *GE* program	0.706***	0.495***
	(0.246)	(0.051)
Top-10% in the CCMP compet.	0.523**	0.355***
	(0.266)	(0.069)
N	193	193

Notes: The table refers to the same sample of students as Figure 1. 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: Inequalities in access to star classes and in performance between high- and low-income students—Prep program L

	(1)	(2)	(3)
	Means		Differences
Variable	High-income students	Low-income students	High- vs low-income students
End-of-high school exam score	1.656	1.623	-0.033
	(0.532)	(0.524)	(0.094)
End of the 1st year ranking	48.021	66.450	18.430***
	(28.427)	(26.515)	(5.007)
Star class	0.505	0.270	-0.234***
	(0.501)	(0.450)	(0.088)
GE selectivity level	16.646	26.462	9.816**
	(21.897)	(26.303)	(4.014)
GE selectivity level – netting out the effect of star classes	29.411	33.300	3.888
	(18.828)	(23.679)	(3.483)
Tier-1 *GE* program	0.697	0.459	-0.238***
	(0.461)	(0.505)	(0.083)
Tier-1 GE program – netting out the effect of star classes	0.341	0.269	-0.072
	(0.391)	(0.428)	(0.071)
Top-10% in the CCMP compet.	0.417	0.216	-0.201**
	(0.494)	(0.417)	(0.086)
Top-10% in the CCMP compet. – netting out the effect of star classes	0.154	0.075	-0.079
	(0.433)	(0.384)	(0.076)
Observations	218	37	255

Notes: The table refers to all students enrolled in the first year of prep program L (*MPSI* classes) between 2011–2012 and 2013–2014. The table compares high- and low-income student high school graduation results (row 1), end of the first year ranking (row 2), admission into a star class after the first year (row 3), selectivity of the *GE* program in which they are admitted at the end of their preparation (rows 4 and 5), probability of being admitted to a Tier-1 program (rows 6 and 7), and probability of scoring within the top-10% of the CCMP competition (rows 8 and 9).
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table 5: Inequalities in access to star classes and in performances between high- and low-income students—All prep programs

	(1)	(2)	(3)
	Means		Differences
Variable	High-income students	Low-income students	High- vs low-income students
Panel A: Top 10 most prestigious prep programs			
End-of-high school exam score	1.643	1.667	0.024
	(0.588)	(0.609)	(0.026)
Star class	0.585	0.504	-0.081***
	(0.493)	(0.500)	(0.022)
Top-10% in the CCMP compet.	0.433	0.342	-0.091***
	(0.496)	(0.475)	(0.022)
Top-10% in the CCMP compet. – netting out the effect of star classes	0.162	0.108	-0.053***
	(0.433)	(0.407)	(0.019)
Observations	2,247	676	2,923
Panel B: All prep programs			
End-of-high school exam score	1.288	1.137	-0.151***
	(0.651)	(0.717)	(0.012)
Star class	0.464	0.316	-0.148***
	(0.499)	(0.465)	(0.009)
Top-10% in the CCMP compet.	0.178	0.088	-0.090***
	(0.382)	(0.283)	(0.006)
Top-10% in the CCMP compet. – netting out the effect of star classes	0.069	0.014	-0.056***
	(0.354)	(0.262)	(0.006)
Observations	8,824	4,496	13,320

Notes: The table refers to all students enrolled in the first year of a prep program in France (*MPSI* classes) between 2011–2012 and 2013–2014, and that participated in the CCMP competition at the end of their preparation. Panel A focuses on the top-10 most prestigious prep programs, and Panel B refers to all French prep programs. The table compares high- and low-income student high school graduation results (row 1), end of the first year ranking (row 2), admission into a star class after the first year (row 3), and probability of scoring within the top-10% of the CCMP competition (rows 4 and 5). * significant at 10%. ** significant at 5%. *** significant at 1%.

Appendix A

1. Proof of proposition 1:

When there is no tracking, by making the change of variable $S = s - a_0$, we have $P^+ = 2P\left(cr + v > S, r > \frac{1}{2}\right)$ and $P^- = 2P\left(cr + v > S, r \leq \frac{1}{2}\right)$ where S is the solution of the *numerus clausus* constraint $P(cr + v > S) = P_0$.

When there is tracking but b is negligible, by making the change of variable $S = s - a_0 - a_1$, we have $P^+ = 2P\left(cr + v > S - b, r > \frac{1}{2}\right)$ and $P^- = 2P\left(cr + v > S, r \leq \frac{1}{2}\right)$ where S is now the solution of the *numerus clausus* constraint $P\left(cr + v > S - b, r > \frac{1}{2}\right) + P\left(cr + v > S, r \leq \frac{1}{2}\right) = P_0$.

Hence, when $b = 0$, the definition of S, P^+, and P^- is the same whether there is tracking or not. In such a case, tracking has no effect on the profile of those admitted into top programs, regardless of its overall effect (a_1) on students.

When b is positive, tracking has no effect either if v can be neglected.

In this case, if there is tracking, we can write, $P^+ = 2P\left(cr > S - b, r > \frac{1}{2}\right)$ and $P^- = 2P\left(cr > S, r \leq \frac{1}{2}\right)$, where S is now given by $P\left(cr > S - b, r > \frac{1}{2}\right) + P\left(cr > S, r \leq \frac{1}{2}\right) = P_0$. Given that P_0 is assumed to be smaller than $\frac{1}{2}$, we necessarily have $\frac{S-b}{c} < \frac{1}{2}$ (or the *numerus clausus* constraint would not be satisfied) and, consequently, $P^+ = 2P_0$ and $P^- = 0$.

In the same case, if there is tracking, we can write, $P^+ = 2P\left(cr > S, r > \frac{1}{2}\right)$ and $P^- = 2P\left(cr > S, r \leq \frac{1}{2}\right)$, where S is given by $P(cr > S) = P_0$. Again, given that P_0 is smaller than $\frac{1}{2}$, we necessarily have $\frac{S}{c} < \frac{1}{2}$ (or the *numerus clausus* constraint could not be satisfied) and, consequently, $P^+ = 2P_0$ and $P^- = 0$, namely the same outcome as when there is tracking.

Finally, when b is negative, tracking can affect inequalities, even when v is negligible. Specifically, when b is negative and v is negligible, the *numerus clausus* constraint is still written $P\left(cr > S - b, r > \frac{1}{2}\right) + P\left(cr > S, r \leq \frac{1}{2}\right) = P_0$ and it implies that $\frac{S}{c}$ is smaller than $\frac{1}{2}$ as long as $P\left(r > \frac{1}{2} - \frac{b}{c}\right) < P_0$, namely as long as $\frac{b}{c} < P_0 - \frac{1}{2}$. Hence, when $\frac{b}{c}$ is sufficiently negative, we have $P^- > 0$, $P^+ < 2P_0$ and tracking contributes to reducing inequalities. In this case, the best non-star students are admitted to top programs, but not the weakest star students. As a consequence, the admission gap between top- and bottom-half students is weaker when there is tracking compared with when there is no tracking.

2. The partial derivative of $S(b, c)$ with respect to b

When b is positive and v is nonnegligible, the *numerus clausus* constraint is written:

$$\frac{1}{c}\left(\int_{S-b-c}^{S-b-\frac{c}{2}} F_v(t)\, dt + \int_{S-\frac{c}{2}}^{S} F_v(t)\, dt\right) = 1 - P_0,$$

which defines implicitly S as a function of b and c, namely $S(b,c)$.

With these notations, the partial derivative of $S(b,c)$ with respect to b satisfies:

$$\left(S_b' - 1\right)\left(F_v\left(S - b - \frac{c}{2}\right) - F_v\left(S - b - c\right)\right) + S_b'\left(F_v\left(S\right) - F_v\left(S - \frac{c}{2}\right)\right) = 0.$$

Denoting $A = F_v\left(S - b - \frac{c}{2}\right) - F_v\left(S - b - c\right)$ and $B = F_v\left(S\right) - F_v\left(S - \frac{c}{2}\right)$, we have $A > 0$, $B > 0$, and $S_b' = \frac{1}{1+B}$ is in $(0,1)$.

Appendix B

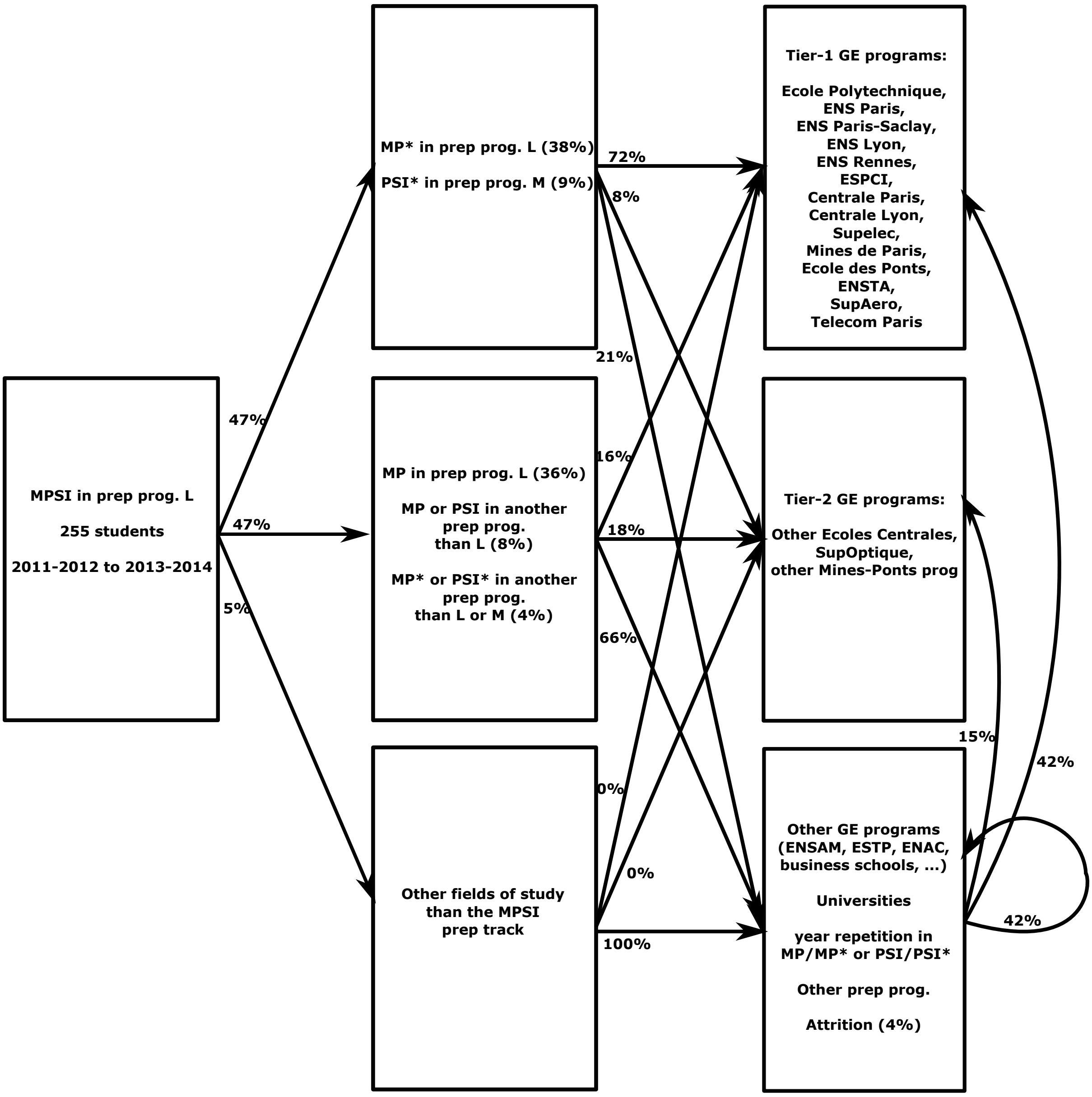


Figure B1: Schooling trajectories of students enrolled in prep program L (*MPSI* classes)

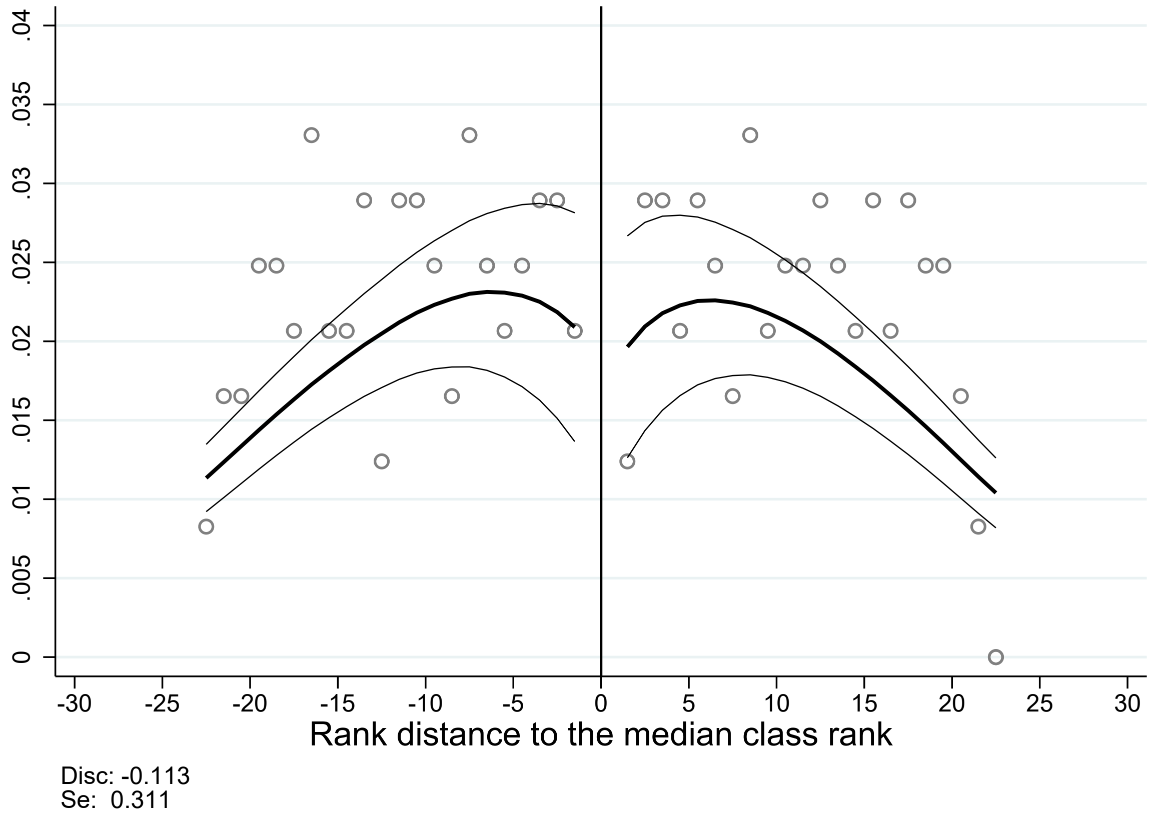


Figure B2: Density of observations around the median class rank

Notes: The table refers to all students enrolled in the first year of prep program L (*MPSI* classes) between 2011–2012 and 2013–2014, excluding students whose first-year ranking fell within –1 to 1 seats of the median class rank. 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.

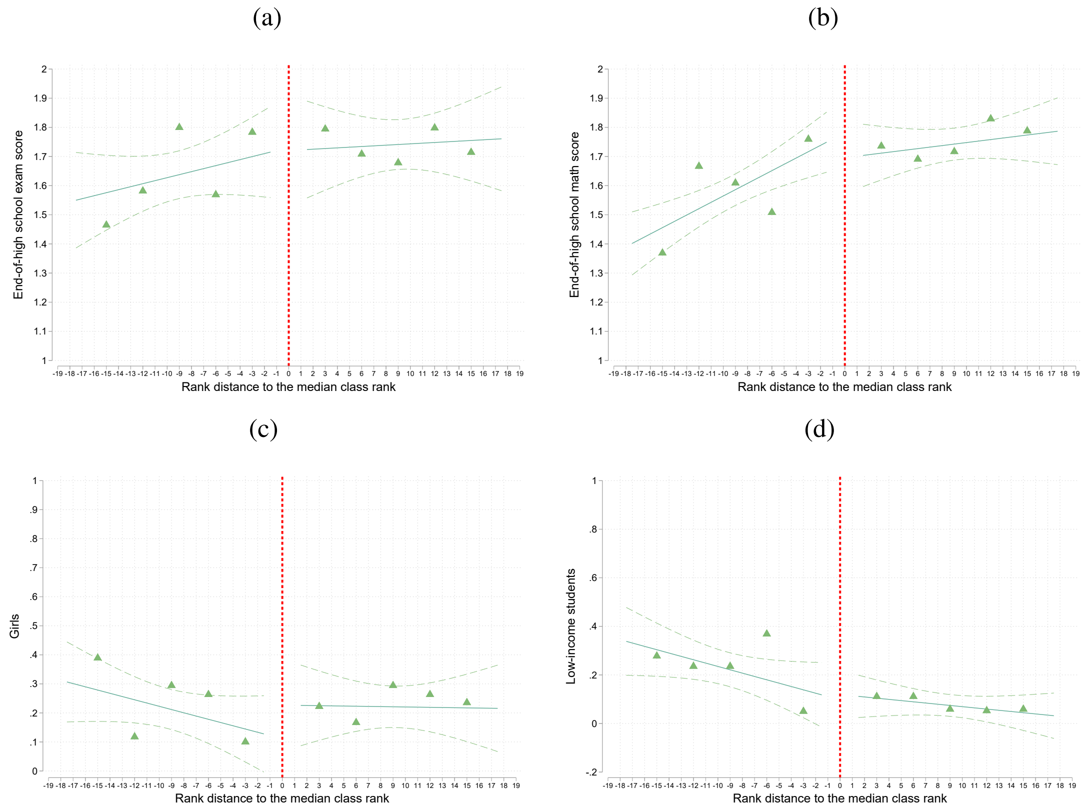


Figure B3: End-of-first-year ranking and student baseline characteristics

Notes: The figure refers to the same sample as Figure 1, and 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 students with the lowest ranks and about 10% among students with the highest ranks.

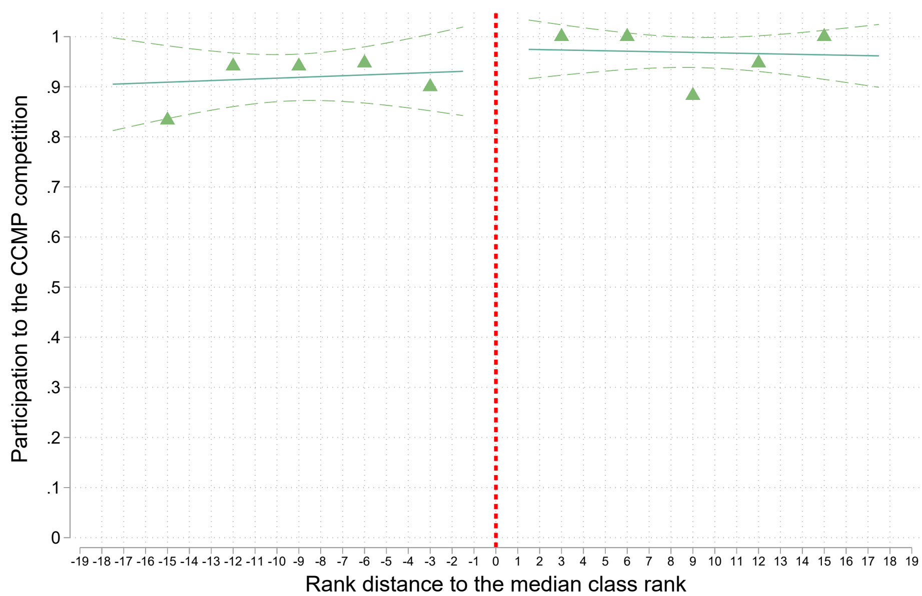


Figure B4: End-of-first-year and participation to the CCMP competition

<u>Notes:</u> The figure refers to the same sample as Figure 1, and shows the proportion of students that participated in the CCMP competition, plotted against their final ranking at the end of the first year (with the median class rank as the origin). Above and below the median class rank, about 95% of students participated in the CCMP competition.

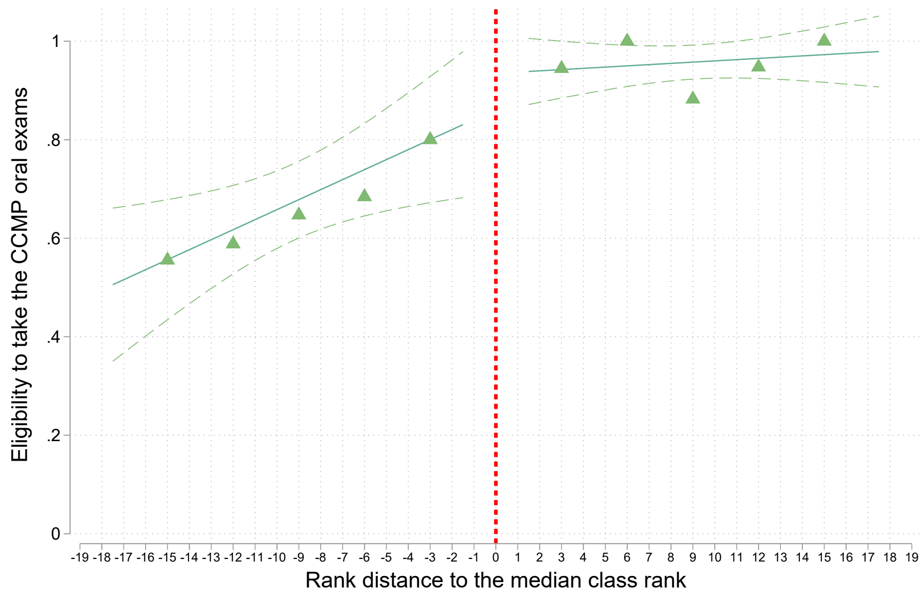


Figure B5: End-of-first-year ranking and eligibility to take the CCMP oral exams

Notes: The figure refers to the same sample as Figure 1, and shows the proportion of students that were eligible to take the CCMP (i.e., students that scored among the top-33% at the CCMP written exams), plotted against their final ranking at the end of the first year (with the median class rank as the origin). Above and below the median class rank, about 90% of students were eligible to take the CCMP oral exams.

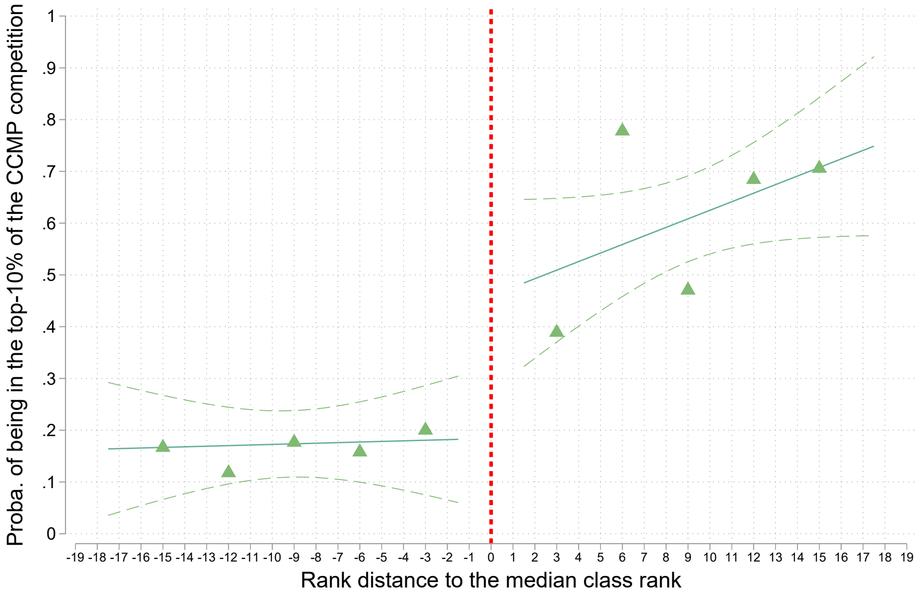
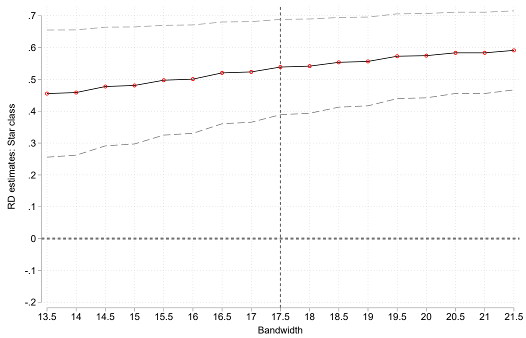


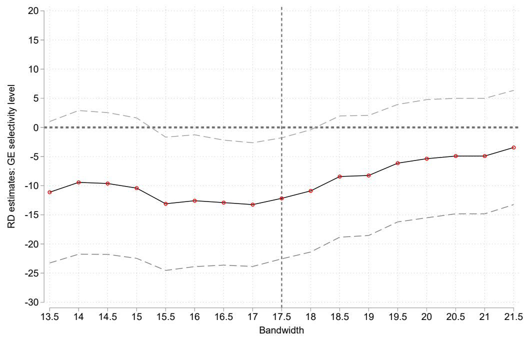
Figure B6: End-of-first-year and probability to score among the top-10% of the CCMP competition

Notes: The figure refers to the same sample as Figure 1, and shows the proportion of students that scored among the top-10% of the CCMP competition, plotted against their final ranking at the end of the first year (with the median class rank as the origin). Below the median class rank, about 20% of students reached the top-10% of the CCMP competition, whereas this proportion is around 50% above the median class rank.

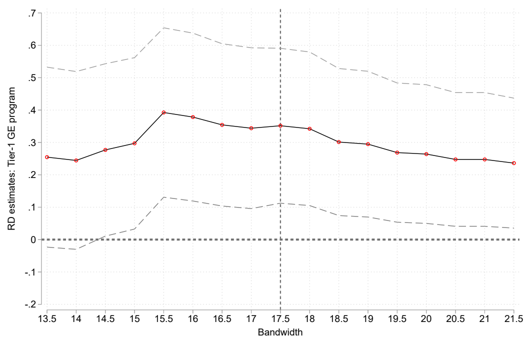
(a) Probability of being admitted to a star class



(b) *GE* selectivity level



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



(d) Probability of scoring in top-10% of the CCMP

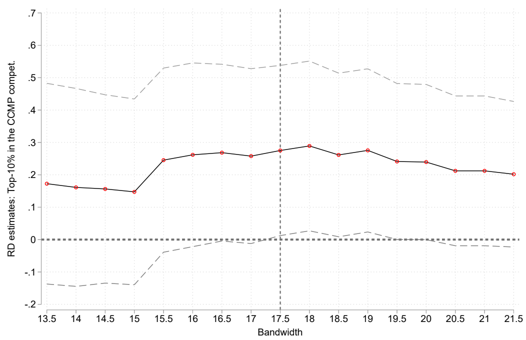


Figure B7: Robustness to bandwidth selection

Notes: The figure refers to all students enrolled in the first year of prep program L (*MPSI* classes) between 2011–2012 and 2013–2014, excluding students whose first-year ranking fell within –1 to 1 seats of the median class rank. 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 selectivity level of the *GE* programs into which students are admitted at the end of their preparation (as measured by the score described in Table B2), (c) presents the estimated effect on the probability of being admitted to a Tier-1 *GE* program, and (d) reports the estimated effect on the probability of scoring among the top-10% of the CCMP 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.

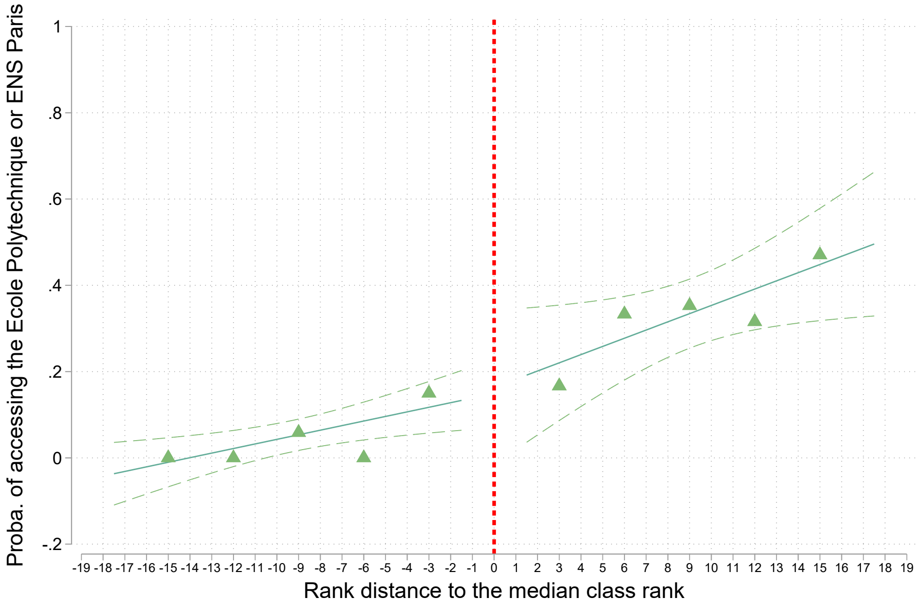


Figure B8: End-of-first-year and admission into the top two *GE* programs

Notes: The figure refers to the same sample as Figure 1, 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.

Table B1: Descriptive Statistics

	Students in prep program L
High school grad. with high honors	0.839
	[0.368]
End-of-high school exam score	1.65
	[0.53]
End-of-high school math 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 (*MPSI* 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 B2: Measuring student performance during the competitive exams using information on the *GE* program to which they are admitted

	GE selectivity level	Mean perc. rank in the 1^{st} year
Polytechnique/ENS Paris	1.5	22.650
ENS Lyon/Mines de Paris/Ponts/Centrale Paris	5.2	40.120
ENS Paris-Saclay/ESPCI/Supelec/Telecom Paris/ENSTA/SupAero	9.8	52.643
ENS Rennes/ENSAE/Centrale Lyon	13.5	56.872
Other Mines-Ponts programs/other Écoles Centrales/SupOptique	18.1	73.497
Other *GE* programs	41.5	79.145
Other types of study	81.0	81.913
Observations		255

Notes: For each program, the first column indicates the average total rank of students admitted in such programs (in centiles). For example, given the total number of applicants and the number of seats offered at *École Polytechnique* and *ENS Paris*, students have to score among the top 3.1% of applicants to gain access to these *GE* programs, which corresponds to an average final ranking of about 1.5. The second column indicates the average first-year ranking (in centiles) of students who were admitted in each program among students enrolled in prep program L. For example, students from prep program L who enrolled in *École Polytechnique* or *ENS Paris* have on average a first-year percentile ranking of 23 (in other words, they ranked on average about 11 out of 46 students).

Table B3: 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 exam score	0.045	1.642	193
	(0.120)		
End-of-high school math 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 1 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 cutoff 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 B4: Star class effects by gender and low-income status

	Star class	*GE* selectivity level	Tier-1 *GE* program	Top-10% in the CCMP compet.
Panel A: Low-income students				
1^{st} year rank > median class rank	0.644***	-5.353	0.189	0.116
	(0.156)	(18.497)	(0.376)	(0.347)
Mean below the median class rank	.276	21	.517	.241
N	29	29	29	29
Panel B: High-income students				
1^{st} year rank > median class rank	0.507***	-16.375***	0.423***	0.319**
	(0.086)	(5.352)	(0.129)	(0.145)
Mean below the median class rank	.5	14.5	.732	.415
N	164	164	164	164
Panel C: Girls				
1^{st} year rank > median class rank	0.388**	-22.254*	0.522*	0.047
	(0.196)	(12.006)	(0.294)	(0.296)
Mean below the median class rank	.405	16.6	.69	.31
N	42	42	42	42
Panel D: Boys				
1^{st} year rank > median class rank	0.557***	-11.509**	0.336**	0.364**
	(0.082)	(5.789)	(0.137)	(0.149)
Mean below the median class rank	.483	15.1	.702	.411
N	151	151	151	151

Notes: The table refers to the same sample of students as Figure 1 or Table 1. The table shows similar results as Table 1 and Table 2 by gender and low-income status. Each row corresponds to a specific sample: low-income students (Panel A), high-income students (Panel B), girls (Panel C), boys (Panel D); and each column corresponds to a specific dependent variable: admission to a star class (column 1), selectivity level of the *GE* program in which students are admitted at the end of their preparation as measured by the score described in Table B2 (column 2), a dummy indicating admission to a Tier-1 *GE* program (column 3), and a dummy indicating whether students scored within the top-10% of the CCMP competition (column 4). Each cell corresponds to a specific regression and reports the estimated impact of falling just above the median class rank during the first year of preparation on the dependent variable at the top of the column. Standard errors are in parentheses, and all regressions include controls selected by the double lasso approach among students' high school graduation results, first-year results, age, gender, low-income status, boarding status; a full set of cutoff dummies; and a first-order spline function of the running variable. This table shows that a student's probability of being admitted to a Tier-1 *GE* program increases by about 42 percentage points for high-income students just above the median class rank, whereas the estimated effect for low-income students is about half as low and non-significant.
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table B5: Robustness to the choice of control variables and functional forms

	Star class		*GE* selectivity level		Tier-1 *GE* program		Top-10% in the CCMP compet.	
Panel A: Robustness to control variables								
	No controls	All controls	No controls	All controls	No controls	All controls	No controls	All controls
1st year rank > median class rank	0.526***	0.536***	-13.316**	-11.648**	0.372***	0.331**	0.275**	0.248*
	(0.080)	(0.082)	(5.363)	(5.608)	(0.127)	(0.128)	(0.137)	(0.141)
Observations	193	193	193	193	193	193	193	193
Panel B: Robustness to functional forms								
	Optimal poly.	Local linear	Optimal poly.	Local linear	Optimal poly.	Local linear	Optimal poly.	Local linear
1st year rank > median class rank	0.289**	0.526***	-13.316**	-13.316**	0.372***	0.372***	0.275**	0.275**
	(0.142)	(0.110)	(5.363)	(5.555)	(0.127)	(0.125)	(0.137)	(0.134)
Degree of opt. poly.	2		1		1		1	
Observations	193	193	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), selectivity level of the *GE* program in which students are admitted at the end of their preparation as measured by the score described in Table B2 (columns 3 and 4), a dummy indicating admission to a Tier-1 *GE* program (columns 5 and 6), and a dummy indicating whether students scored within the top-10% of the CCMP competition (columns 7 and 8). 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, 5, and 7), or with control variables for all available students' baseline characteristics (columns 2, 4, 6, and 8). The second row shows similar results to the analysis in Table 1 and Table 2 with alternative functional forms, that is, columns 1, 3, 5, and 7 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, 6, and 8 report the results using local linear estimations. Standard errors clustered at the individual level in parentheses.
* significant at 10%. ** significant at 5%. *** significant at 1%.

Table B6: Star class and performance in the CCMP competition

	All prep programs	Top-10 prep programs
Star class	0.234***	0.463***
	(0.006)	(0.017)
Mean	0.147	0.412
Observations	13320	2923

Notes: The table refers to all students enrolled in the first year of a prep program in France (*MPSI* classes) between 2011–2012 and 2013–2014, and that participated in the CCMP competition at the end of their preparation. Panel A refers to all French prep programs, and Panel B focuses on the top-10 best-performing prep programs. The table shows the results when regressing a dummy indicating whether students scored within the top-10% of the CCMP competition on a variable indicating whether students are enrolled in a star class, while controlling for gender, low-income status, high school graduation results, and prep program fixed effects.
* significant at 10%. ** significant at 5%. *** significant at 1%.