# Price of Admission: The Impact of Application Fees on STEM Graduate School Applicants

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**Abstract**

This study examines the impact of application fees on the application behavior, admission, and enrollment outcomes of STEM graduate school applicants in France. Using a Regression Discontinuity Design and data from the centralized admission process to STEM graduate schools from 2015 to 2021, the findings indicate that candidates required to pay application fees submit fewer applications, resulting in adverse admission outcomes. Counterfactual simulations of the school-student matching algorithm indicate that eliminating the fee waiver would decrease by 13% the representation of low-income students admitted in STEM graduate schools. The effect of application fees is particularly pronounced among male students, and those from lower socio-economic backgrounds. Fee-paying candidates are less likely to enroll in a STEM graduate school in the three subsequent academic years, and more likely to be enrolled in university programs. However, they enroll in programs that are equally selective and seem to offer comparable labor market prospects.

# 1 Introduction

Substantial inequalities are still observed in access to higher education and in particular in access to selective higher education. In the U.S., for instance, children with parents in the top 1% of the income distribution are 77 times more likely to attend elite colleges and universities than children with parents in the bottom 20% of the income distribution (Chetty et al., 2020). Strong inequalities are also observed in France, where the higher education system is particularly segregated. For example, high socioeconomic status students represent 78% of student enrollment in the most selective graduate schools in France, while only representing 23% of an age cohort (Bonneau et al., 2021).

In explaining these inequalities, the literature has identified several contributing factors. These can be categorized into: (i) financial constraints, with key studies surveyed in Dynarski et al. (2023b); and (ii) non-financial constraints, comprehensively reviewed in Dynarski et al. (2023a). Among financial constraints, tuition fees, student loans, and financial aid have received considerable attention. However, these are not the only fees that applicants incur in higher education; many programs, particularly at the graduate level, also levy application fees. The impact of application fees has been much less studied. Studying these fees seems particularly important for two reasons. First, application fees to graduate programs are a common practice in many parts of the world: examples include Chile, India, Japan, Italy, Spain, U.K., Vietnam, etc.[1] In the U.S., students are often required to pay a non-refundable fee, usually ranging from \$50 to \$100, to apply for undergraduate and graduate programs.[2] Application fees are also common for most standardized tests such as the GRE, TOEIC, TOEFL international tests, JEE in India, LNAT and TMUA in the U.K., SAT and ACT in the U.S., etc.[3] Second, the literature

[1]See example of application fees for Chile: https://www.ing.uc.cl/en/programas-de-estudio/postgrado/magister-ciencias-la-ingenieria/requisitos-y-postulacion/, for India https://iisc.ac.in/admissions/fees-and-scholarships/, for Japan https://www.iuj.ac.jp/gsim/im-admission/how-to-apply/imintadm6/, for Italy https://www.polimi.it/en/international-prospective-students/laurea-magistrale-programmes-equivalent-to-master-of-science/application-procedures/application, for Spain https://bse.eu/admissions/how-to-apply, for the U.K: https://ukuni.net/articles/these-uk-universities-charge-application-fees, and for Vietnam: https://oisp.hcmut.edu.vn/en/admission/apply-online.

[2]For students in the U.S., the average application fee for undergraduate programs stands at \$56, while graduate programs typically charge an average of \$66 per application. Applications to Ivy League institutions command a higher price, averaging around \$76 per application. See this webpage (https://www.bestcolleges.com/research/college-application-fees-how-much-does-it-cost/) for examples of application fees to specific U.S. higher education institutions.

[3]GRE: https://www.ets.org/gre/test-takers/general-test/register/fees.html, TOIEC: https://www.examenglish.com/TOEIC/index.php , TOEFL: https://www.ets.org/toefl/test-

has established that when making their higher education application decisions, individuals are sensitive to small changes such as the availability of a test-taking center (Bulman, 2015), the cost of sending a test report (Pallais, 2015), or receiving in-school application assistance (Oreopoulos and Ford, 2019). Additionally, most research on financial constraints focuses on the United States or the United Kingdom, with only a small literature examining the continental European context.

In this paper, I address this gap by studying the impact of application fees on the application behavior and admission outcomes of STEM graduate school candidates in France. French higher education is composed of two distinct academic pathways: university programs, which are usually non-selective, and elite graduate schools (*Grandes Écoles*), which are much more selective. Over the period 2015-2021, the average percentile rank at the high school graduation exam (*Baccalauréat*) was 53 for university students versus 75 for STEM graduate school students. Most public universities in France do not levy application fees, although elite graduate schools usually do. This is because the admission process for these institutions involves comprehensive competitive exams with multiple written and oral tests, leading to high costs that are partially covered by the application fees. These competitive entrance exams take place two to three years after high school, and students first enroll in intense academic programs known as *Classes préparatoires aux Grandes Écoles* (hereafter prep programs) to prepare for those exams. The study leverages this unique context characterized by high application fees (averaging around 1,000 euros),[4] varying fee structures,[5] and the availability of low-income fee waivers governed by clear eligibility rules common to all programs. This context provides an ideal setting for a regression discontinuity design along the fee waiver threshold to observe the causal effects of application fees on the application behavior, admission, and enrollment outcomes of candidates to STEM graduate programs.

The main research question this study aims to address is: How do application fees influ-

takers/ibt/register/fees.html, JEE: https://jeeadv.ac.in/regfee.html LNAT: https://lnat.ac.uk/registration/paying-for-your-test/ TMUA: https://www.undergraduate.study.cam.ac.uk/apply/how/maths-admission-test, SAT: https://satsuite.collegeboard.org/sat/registration/international-testing/fees, ACT: https://www.act.org/content/act/en/products-and-services/the-act/registration/fees.html.

[4]From 2015 to 2023, the average application fees paid by fee-paying candidates were 989 euros. The average fee has increased over time, rising from 912 euros in 2015 to 1,007 euros in 2021 (all amounts are in 2021 constant euros).

[5]Some application fees are specific to one graduate school, while others apply to a group of graduate schools.

ence the application behavior of students, and do these fees lead to adverse admission and enrollment outcomes?

To answer this question, I rely on novel administrative data from the centralized admission process to STEM graduate schools in France from 2015 to 2021. This dataset includes students' application decisions, application fees paid, need-based grant status — which makes students eligible for an application fee waiver —, competitive entrance exam results, and admission outcomes. Additionally, I incorporate data on need-based grant applications to observe students' positions relative to the fee waiver threshold. This allows for a regression discontinuity analysis at the margin of fee waiver eligibility, comparing students on either side of the threshold who are otherwise similar. This comparison enables estimation of the causal impact of application fees on application decisions and admission outcomes. Furthermore, I use enrollment data covering nearly all French higher education to observe enrollment patterns for both STEM graduate school students and those who choose other programs, particularly university programs, and to track them until graduation.

The main results show that having to pay application fees induces a significant decrease in the number of entrance exams attempted by candidates. Considering the full universe of applicants, students who benefit from an application fee waiver pay substantially lower amounts (€60 vs. €989) than those required to pay fees and also take many more entrance exams (24 vs. 15), which corresponds to applying to more STEM graduate schools (84 vs. 62). Additionally, the number of exams taken by students who have to pay fees varies by their parents' socio-economic status (SES):[6] among fee-paying applicants, high SES individuals take more entrance exams than low SES individuals (15 vs 8), suggesting that some individuals are somewhat constrained in the number of entrance exams they can take.[7] Specifically, at the margin of the fee waiver, regression discontinuity results show that candidates required to pay application fees

[6]For socio-economic status, I rely on the Department of Education's statistical service (DEPP), which classifies occupations into four groups by socio-economic status (SES): High SES includes professionals, managers, CEOs, teachers, professionals, and artists; Upper-middle SES includes intermediate occupations, technicians, foremen, and supervisors; Lower-middle SES includes farmers, artisans, shopkeepers, and white-collar employees; Low SES includes blue-collar workers and non-working people. The SES of the child's legal representative is used for classification.

[7]The proportion of fee-waiver (low-income) students is correlated with parental socio-economic status, though not perfectly, as (i) other factors (such as the number of siblings and distance to the program) intervene in the fee waiver formula, and (ii) SES is based on parental occupation, not parental income. For instance, 15% of high SES individuals are fee-waiver students, compared to 65% of low SES individuals

attempt, on average, 13 fewer entrance exams than those who are exempted, representing a 55 percent reduction. This corresponds to applying to 23 fewer STEM graduate schools, representing a 30 percent reduction.

In theory, changes in application behavior could have ambiguous effects on admission chances: fee waiver students might have increased admission chances because they submit more applications, but they might also have lower chances because taking more exams could potentially reduce their performance. However, I observe that application fees have real effects on admission chances, and the first mechanism — submitting more applications — prevails. At the fee waiver eligibility threshold, the probability of receiving an admission offer from a STEM graduate school decreases by 11.1 percentage points for fee-paying candidates, representing an approximately 15 percent reduction. Results from counterfactual simulations of the school-student matching algorithm, assuming the removal of the fee waiver and thus a reduction in the number of applications from low-income students, suggest that the proportion of low-income students admitted to STEM graduate schools would decrease by 3.3 percentage points (p.p.) overall, representing a 13 percent reduction, and by 4.1 p.p. (23 percent reduction) in the most selective schools.

The fee waiver is granted to need-based grant students (*Boursiers sur critères sociaux*). This status not only offers application fee waivers but also provides financial aid of approximately 1,000 euros per year and tuition fee waivers at public institutions. These multiple benefits complicate isolating the impact of application fees. In the paper, I perform a number of tests which suggest that application fees, rather than tuition fees, primarily influence students' application choices.[8]

Despite the fact that application fees reduce low-income students' probability of being admitted to STEM graduate schools, I do not find that they affect their probability of pursuing graduate studies in general, nor the average selectivity of the programs they attend. However, students are less likely to enroll in STEM graduate schools — particularly male students — and more likely to enroll in university programs — especially female students. Aligned with no

[8]For instance, I observe that among applications to public schools, the only programs granting tuition fee waivers, the average sticker price of tuition for candidates on both sides of the threshold is similar, suggesting that students do not heavily consider tuition fees when applying to public STEM graduate schools. However, they might consider it for private programs, which are much more expensive but do not grant tuition fee exemptions (although they grant application fee exemptions).

observed difference in program selectivity, aggregated earnings data at the program $\times$ cohort level reveal that expected earnings one year after graduation does not vary significantly at the application fee waiver threshold. However, it is important to note that outcomes might differ when considering individual labor market data over a longer period. This lack of change in selectivity, despite university programs being less selective on average than STEM graduate schools, can be attributed to two factors: (i) fee-paying candidates who enroll in STEM graduate schools tend to choose more selective institutions, and (ii) the student population in question is highly informed, consisting mainly of high-SES and high-ability individuals capable of targeting quality university programs, particularly at the master's level. As the regression discontinuity design yields a local average treatment effect, the lack of observed impact on enrollment and program selectivity might also mean that the fee waiver is optimally set within the parental income distribution, where informed individuals can easily transition to comparable programs.

The effect of application fees on students' application, admission, and enrollment reveals substantial heterogeneity. Having to pay application fees disproportionately impacts male students, individuals from a lower socio-economic background, or with lower prior academic achievements. The gender heterogeneity observed is mostly explained by the fact that when having to pay fees, male students reduce more the number of graduate schools they apply to and particularly opt for schools with higher selectivity, thus foregoing their *safety choice*. In contrast, female students tend to lower the maximum selectivity of the schools they apply to, thereby eliminating their *ambitious choice*. I present a conceptual framework encompassing application sets with and without application fees for both risk-averse and risk-neutral students, which rationalizes these findings to the extent that women are more risk-averse than men in their higher education decisions, a result supported by previous literature (Saygin, 2016; Dohmen et al., 2011; Filippin, 2022). When comparing graduate schools with decentralized versus centralized fee schemes, the eviction effect at the fee waiver threshold is significantly more pronounced for entrance exams requiring applicants to pay a specific amount for each school, as opposed to a fixed amount for multiple schools.

**Related Literature and Contributions.** While numerous studies have analyzed the impacts of various financial barriers on access to and success in higher education, relatively few have specifically addressed the role of application fees. The majority of the existing literature focuses on the impacts of tuition fees, living costs, and the availability of financial aid, including grants and loan programs, on students' choices and success in higher education.

There is still a significant debate regarding the impact of tuition fees on student enrollment and completion. Most studies focused on the US context have found a correlation between price and college enrollment, choice, and persistence (Hemelt and Marcotte, 2011; Denning, 2017). However, recent studies examining the UK's tuition increase have found no effect on enrollment, nor on disparities in enrollment by socio-economic status (Murphy et al., 2019). Similarly, Bucarey (2018) found that the introduction of tuition-free policies in Chile could lead to a 20% reduction in the enrollment of poor students, attributed to increased demand for selective programs by wealthier students. In another European context, debates continue regarding the impact of recent tuition increases and subsequent decreases in some German Länder. Hübner (2012) initially found a negative effect on enrollment, contrasting with more recent studies which observe no effect from these reforms (Bruckmeier and Wigger, 2014; Bietenbeck et al., 2023).

The impact of financial aid on students' enrollment, persistence and graduation in higher education is more consensual, with the vast majority of studies finding positive effect of financial aid, in particular for low-income students. For instance, a seminal study by Dynarski (2003) found that the availability of financial aid significantly increased the probability of college enrollment and completion among low-income students in the United States. Similarly, Bettinger (2004); Angrist et al. (2022) found that in the US, increases in financial aid led to significant increases in college enrollment and persistence among low-income students. In the French context, Fack and Grenet (2015) also show that financial aid increase low-income student enrollment and degree completion. More recently, Denning et al. (2019) found that in Texas, the Pell Grant not only affect college enrollment but also lead to higher earnings, and this increase in earnings means that financial aid likely pays for itself several times over. Recent studies have nevertheless observed that the impact of financial aid is less clear when targeting high ability students (Kenedi, 2023) or not attached with academic requirement (Montalbán, 2023).

However, the literature addressing the impact of application fees on students' decision-making processes and their subsequent outcomes in higher education remains sparse. Noteworthy exceptions include the studies conducted by Pallais (2015) and Smith et al. (2015). Pallais (2015) shows that a reduction of \$6 in the cost of sending ACT score reports significantly increased the number of reports sent by students, diversified the range of colleges to which students applied, and notably improved the chances for low-income ACT takers to gain admission into more selective institutions. This study undermines the dual effect of application fees: they can be a *financial barrier* per se, but the limited number of free sending reports also serves as a rule-of-thumb that constitutes a *cognitive barrier*, subsequently leading students to make sub-optimal application choices. Smith et al. (2015) investigated how changes in the cost of applications — either through a direct application fee increase (\$10 on average) or the indirect cost of additional requirements, such as writing an essay — affect student behavior. Using aggregated application and enrollment data at the college level, their findings indicate that even minor cost increases can lead to a decrease in the number of applications submitted, albeit with minimal impact on actual enrollment rates.

My study also relates to the literature on the complexity of admission processes and behavioral barriers (Ross et al., 2013). These barriers can relate to lack of information (Goodman, 2016; Bergman et al., 2019; Gurantz et al., 2020), differences in preferences (Wiswall and Zafar, 2015), differences in self-confidence (Hakimov et al., 2022). There is extensive literature on the impact of minor barriers encountered during the application process, which is comprehensively reviewed in Dynarski et al. (2023a). Notably, this body of work demonstrates that some students apply to too few colleges, thereby diminishing their chances of admission to any program (Smith, 2014). A significant body of experimental and quasi-experimental research, predominantly conducted within the U.S. context, has concentrated on assessing interventions ranging from light-touch to comprehensive strategies aimed at simplifying the application process (Bettinger et al., 2012; Hyman, 2020; Page et al., 2020). Several studies have assessed comprehensive programs designed to enhance access for low-income or individuals at the margin of going to college. One component of these programs is sometimes an application fee waiver (Carrell and Sacerdote, 2017), or assistance with paperwork for obtaining such waivers (Hoxby and Turner, 2015). However, these studies consider the application fee waiver as part of a broader, multidimensional intervention, rather than isolating the impact of application fees themselves.

This work distinguishes itself from the existing literature in several ways. First, the variation in application fees examined in this study is significantly larger than those analyzed in the studies by Pallais (2015) and Smith et al. (2015), which consider changes of $6 and $10, respectively. In contrast, this study investigates application fees that vary by approximately €800 at the application fee waiver threshold under examination, with program-specific fees ranging from €80 to €120. Second, unlike Pallais (2015), which focuses on the costs associated with sending ACT reports, this study exclusively examines the impact of application fees themselves. Third, the population of students considered here are more privileged, both in terms of previous academic achievement and socio-economic status, which suggests that the effects of higher application fees on their decisions and behavior might differ from those observed in the Pallais (2015) and Smith et al. (2015) studies. I also leverage the existence of an application fee waiver, which is based on a simple discretionary rule, creating a stark and sudden change in the amount of application fees paid. This enables a robust assessment of the impact of application fees through a regression discontinuity design. This approach is particularly valuable given the rarity and limited usability of such fee waivers based on a clear and identical rule for all programs. This empirical strategy also complements studies that focus on the effects of changes in the amount of application fees (Smith et al., 2015) rather than the absolute amount. Additionally, the availability of individual-level data allows for the observation of applications for each student, rather than relying on aggregated data. This data is particularly useful for identifying which groups of students are more affected by the presence of application fees and for running counterfactual simulations of the student-program matching algorithm. Last, I exploit the varying application fee structures across STEM graduate school entrance exams to investigate how the design of application fees (either program-specific or common to multiple programs) influences application patterns. These results can provide some insights on the interest of having common application procedure, such as the Common application in the U.S. (Knight and Schiff, 2022).

Considering the significant implications of application decisions on future outcomes, particularly in light of the returns associated with STEM degrees, it seems essential to comprehensively understand the impact of all potential financial barriers, among which application fees.

More broadly, this paper contributes to the literature on financial constraints affecting access to higher education, a field that remains relatively underexplored outside the contexts of the U.S. and U.K.

The remainder of this paper is organized as follows: Section 2 provides an overview of the institutional context of higher education in France, focusing specifically on the application fees associated with entrance exams for STEM graduate schools. Section 3 presents a conceptual framework that discusses the theoretical impact of application fees on two types of students: risk-neutral and risk-averse. Section 4 outlines the data sources used in this study. Section 5 presents the main findings regarding the impact of application fees on students' application behaviors, admission, and enrollment outcomes. Section 6 discusses the findings, and in particular the sensitivity of students to application fees compared to their sensitivity to tuition fees. Lastly, Section 7 concludes.

## 2 Institutional Background

**French Higher Education System.** The French higher education system is characterized by several academically hierarchical tracks. After passing the high school graduation exam (*Baccalauréat*), students can choose between three main tracks (see Figure A1): a vocational track — enrolling around 30 percent of first-year students in 2021-2022 (SIES, 2022) — a non-selective academic track, university — 50 percent of first-year students — and a selective academic track, the *classes préparatoires aux grandes écoles* (hereafter CPGE or prep programs) — enrolling 7 percent of first-year students. The remaining 13 percent are enrolled in other programs such as paramedical training or specialized schools. The coexistence of two academic tracks is a specificity to French higher education. Until 2018, access to university was formally granted to anyone holding a high school graduation diploma. Since then, some programs have introduced selection criteria based on academic performance in high school. However, most university programs remain undersubscribed and, therefore, not selective in practice: Bechichi et al. (2021) estimated that in 2018 and 2019, 84% of university programs are non-selective, in the sense that they refuse less than 5 percent of applicants. In contrast, CPGE programs are highly selective due to the limited number of spots available. Admission to CPGE programs is based on grades and assessments from the junior and senior years of high school. These selective programs attract the highest performing students. For example, in 2016-2017, 43 percent of the students in CPGE had obtained their high school exam with highest honors — i.e., with an average grade above 16/20 — compared to 3 percent of the students in the technical and vocational track and 8 percent of the students at the university (Bonneau et al., 2021). In this paper, I focus on science and technology CPGE,[9] which admit around 25,000 students each year (around two third of all CPGE students), i.e. around 2.5 percent of a birth cohort.

**STEM CPGE.** STEM prep programs are intensive two- to three-year academic programs designed to prepare students for national entrance examinations to STEM elite graduate schools. The workload is very heavy since students must assimilate in two years what would be learned at university in three years, for several subjects. For example, in STEM prep programs, the national curriculum is close to a bachelor's degree in mathematics, physics, chemistry, engineering and/or computer science, depending on the students specialties and options. Students take four to six hours of written mock exams per week, usually on Saturdays, as well as two oral assessments per week, and are regularly ranked against their peers. There are five main tracks in the STEM CPGE programs, with different emphases on mathematics, physics, chemistry, biology or industrial sciences. See Figure B2 for an organization chart of the different STEM CPGE tracks considered in the study. These programs are located in usually prestigious high schools. Overall, there are 205 high schools with STEM CPGE programs. Figure E5(a) shows the distribution of those programs in France.

**Admission process to elite graduate schools (*Grandes Écoles*).** The *Grandes écoles* play a key role in the training of the elite in France. Historically, these prestigious graduate schools were developed after the French Revolution to train a political, economic, science, military or academic elite, selected according to "meritocratic" criteria, as opposed to "aristocratic" ones. In the most recent cohorts, about 6 percent of a generation graduated from one of these prestigious graduate schools and around 3 percent from a STEM one. Within the elite graduate schools, there is a significant hierarchy, with some schools being very selective and others less so. There

[9]There also exists humanities CPGE and business and economics CPGE.

are both public and private institutions (around 30% of institutions are private, enrolling 15% of all STEM graduate school students). The main differences are that public institutions have much lower tuition fees and offer tuition fee waivers for low-income students, unlike private graduate schools. On average, public graduate schools tend to be more selective: the average percentile rank of admitted students is 83 in public schools versus 68 in private STEM graduate schools.

At the end of the two years of STEM prep programs, students take competitive entrance exams to STEM elite graduate schools. More than 200 graduate schools are accessible (see Figure E5(b)), but candidates can choose which schools' exams to take. In order to limit the number of competitive exams, the schools have decided to group into four/five[10] different clusters of competitive exams. The written component of each cluster of competitive entrance exams typically comprises two mathematics tests, two physics tests, a language test, a literature test, and additional tests in chemistry, engineering sciences, or computer science, depending on the candidate's specialties and options.

The admission process to these elite graduate schools is centralized and organized by the *Service de Concours Ecoles d'Ingénieurs* (*SCEI*). The admission process relies on a college proposing version of the Gale Shapley Deferred Acceptance mechanism (Gale and Shapley, 1962). The calendar for the admission process is presented in Figure C3. Students have to decide which competitive exams to take between December and January. They take the written part of the competitive exams in April and May. Eligible candidates, those who have obtained sufficient results in the written tests, take the oral exams in June and July. They have to provide their final ranking of schools to the clearinghouse by the end of July and receive their first offers from the centralized admission process immediately afterwards. There are five rounds of offer and acceptance in the admission process, spanning from the end of July to the beginning of September, due to approximately 20 percent of students repeating the second year of the prep program to improve their entrance exam results, thereby exiting the admission procedure and freeing up their spots for others.

[10] Over the study period, there were five clusters (X-ENS, Mines-Ponts, Centrale Supélec, CCINP, E3A) from 2015 to 2019, and four from 2020 to 2021, with CCINP and E3A having merged.

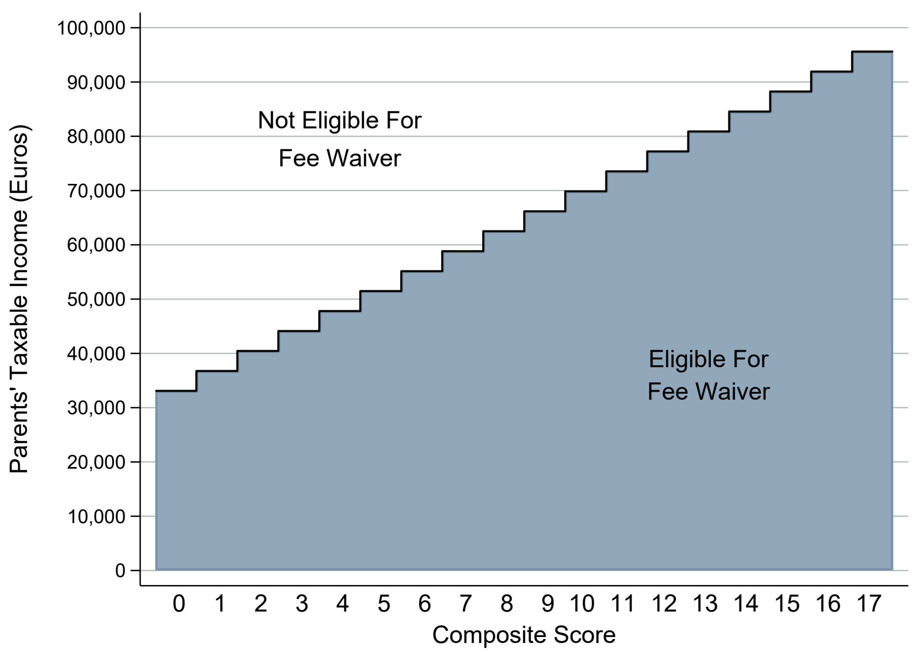
**Application Fees.** Most competitive entrance exams come with an application fee. The organization of all written and oral tests has a high cost, which is partly covered by the fees paid by candidates. The amount of fees paid depends on the choice of exams. Candidates can take as many entrance exams as they wish, with the assurance that there will be no schedule conflict. Fees are calculated based on the number of chosen entrance exams. Some exams grant access to only one school, while others open doors to multiple institutions. The cost for an entrance exam that leads to a single graduate school typically ranges from 50 to 100 euros, whereas exams providing access to several schools vary from 250 to 320 euros.[11] Certain entrance exams operate on a 'hybrid' model, where applicants pay a base amount for the cluster of entrance exams and additional, smaller fees for each specific school they wish to apply to. Crucially, regardless of whether the fee structure is centralized (common fees), decentralized (specific school fees), or hybrid, the exams are always organized into clusters. The required written and oral tests (*épreuves*) remain consistent within each cluster (*banques*), which may contain one or several entrance exams (*concours*), each leading to one or several graduate schools (*grandes écoles*). For a visual representation of the exam clusters, entrance exams, and associated graduate schools, refer to D4 in the Appendix. It is important to note that application fees are charged at the level of the entrance exams, not by the clusters or the specific graduate schools themselves.

Importantly for the analysis, low-income students benefit from fee exemption. For most competitive entrance exams, they are completely exempted from paying application fees and for some entrance exams, usually the less selective ones, they pay significantly reduced amount — between 15 and 50 percent of the full fees. These exemption are granted to need-based grant students (*Boursiers sur critères sociaux*) which is based on parental taxable income and a family needs assessment score computed with the number of siblings, the number of siblings in higher education, and the distance to the higher education program. Figure 1 displays the parental income threshold that qualifies for application fee exemption, for each composite score of family needs assessment. In addition to application fee waivers, need-based grant status provides financial aid (around 1,000 euros per year over my period of study) and tuition fee waivers at public institutions only, complicating the isolation of the impact of application fees. This issue is

[11] See Figure F6 for details on some fees charged in 2020 for track 1 (MP) applicants and this link for complete application fees.

discussed in detail in the empirical strategy and discussion sections, where evidence suggests that application fees, rather than tuition fees, drive changes in students' application portfolios. This is particularly evident in private STEM graduate schools, which grant application fee waivers but not tuition fee waivers. There are 6 other income thresholds at lower parental income levels, which give entitlement to a higher amount of grant, the amount of which depends on the threshold. Importantly, this feature simplifies the process for students, eliminating the need for specific paperwork to benefit from the application fee exemption, as it is directly linked to their need-based grant status. Thus, students are required to have applied for a need-based grant between January and April of the previous academic year.[12] To avail of the waiver, they must present their official document of need-based grant receipt to the administration in charge of the centralized admission process to STEM graduate schools (SCEI). For a detailed timeline of the need-based grant application process, decision timelines, and the schedule for entrance exams, refer to Figure C3.

Figure 1: Income Eligibility Thresholds for Application Fee Waiver




*Notes:* The figure shows the income thresholds for application fee waivers over the period 2011 to 2022. These thresholds are based on the applicant's composite score of family need assessment (x-axis), which in turn depends on the number of siblings, the number of siblings in higher education, and the distance to the registered higher education program. These thresholds are applied to the parents' taxable income earned two years prior to application (y-axis).

[12]To qualify for the need-based grant in the first year of the preparatory program, they must apply during their senior year of high school. Similarly, to benefit from the need-based grant status in the second year of the preparatory program — the critical year when they take high-stakes entrance exams and thus require the fee waiver — they must apply to the need-based grant in the first year of the prep program.

Figure 2 shows the amount of application fees paid, the number of entrance exams taken, and the number of STEM graduate schools to which this corresponds, segmented by fee waiver status and the socio-economic status of the parents. Among fee-paying candidates, students from high-SES backgrounds tend to take more entrance exams; however, no difference is observed by SES among fee-waiver candidates.[13]

**Tuition Fees.** STEM graduate schools charge varying tuition fees depending on whether they are private or public (Figure I9), averaging 7,500 euros for private schools and 1,000 euros for public ones. For most public graduate schools (around two-thirds), the legally set tuition is 601 euros, with some specific schools charging up to 3,500 euros per year. Private school tuition ranges from 3,500 euros to 10,000 euros annually. On average, private programs are less selective, enrolling students with an average national high school exam percentile rank of 68, compared to 83 for public schools. Most students exempt from application fees are also exempt from tuition fees, but only at public schools — a topic discussed further in the Empirical Strategy and Discussion sections.

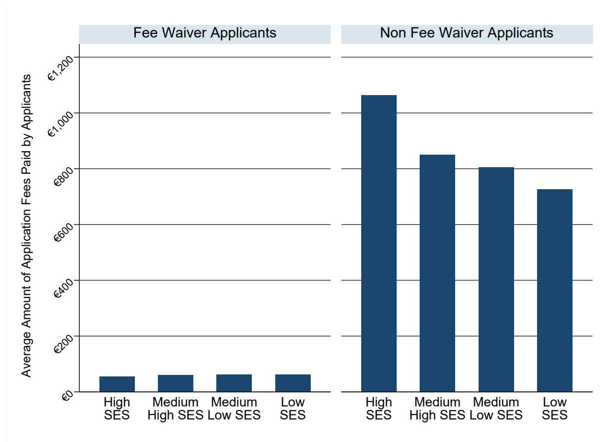
# 3 Conceptual Framework

In this section, I introduce a conceptual framework for graduate school applications that encompasses application fees and integrates students' attitudes towards risk. The aim of this framework is to clarify the setting and furnish insights into the expected impact of application fees on students' application decisions, with some of these insights being validated in the empirical part of the study.

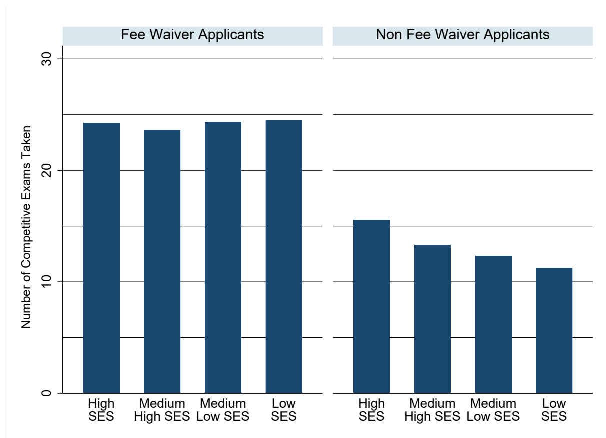
**Setting.** I consider a simplified framework involving $N$ students, each with a known ability $a$, uniformly distributed across the interval $[0, 1]$. I introduce a continuous variable, denoted by $x$, which is associated with graduate school selectivity: higher values of $x$ are associated with greater selectivity. Variable $x$ may be though of as a summary statistics of all the benefits that

[13] Socioeconomic status is determined based on the Department of Education's statistical service (DEPP), which classifies occupations into four groups. Figure G7 displays the same statistics using a more continuous measure of parental background, the SES index (IPS), also defined by the DEPP.

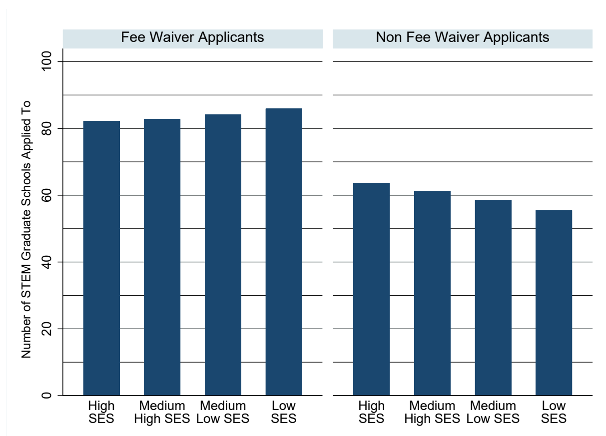
Figure 2: Application Fees and Number of Applications, by Fee Waiver Status and Socio-Economic Status




(a) Application Fees




(b) Number of Entrance Exams Taken




(c) Number of Grad. Schools Applied To

*Notes:* Panel a illustrates the average application fees paid by applicants to elite STEM schools, categorized by socioeconomic status and fee waiver status. Panel b depicts the average number of exams taken by applicants, also categorized by socioeconomic status and fee waiver status. Panel c displays the number of STEM graduate schools applied to, corresponding to the total schools eligible based on the entrance exams taken, irrespective of their inclusion in students' ranked preferences. Socioeconomic status is determined based on the Department of Education's statistical service (DEPP), which classifies occupations into four groups. High socioeconomic status includes professionals, managers, CEOs, teachers, and artists. Medium-high SES encompasses middle occupations, technicians, foremen, and supervisors. Medium-low SES includes farmers, artisans, shopkeepers, and employees. Low SES corresponds to blue-collar workers and inactive individuals. The SES of the child's legal representative is used for classification. Fee waivers are granted based on several criteria: parents' income, distance to the registered higher education program, number of siblings, and number of siblings in higher education. Data are from the SCEI administrative datasets and cover the period 2015-2023.

students derive from attending a graduate school, *e.g.* monetary returns, peer and/or instructor quality. I will focus on two graduate schools, indexed by 1 and 2. School 1 is more selective so that $x_1 > x_2$. The probability of admission to school 1 is lower for all students, regardless of their ability, $0 \leq p_1(a) < p_2(a) \leq 1$ for all $a \in [0,1]$. For notational simplicity, as $a$ is exogenous in this model, I will write $p_1(a)$ as $p_1$ and $p_2(a)$ as $p_2$. There is also an outside option, *e.g.* agents may choose to go to a local university or to study abroad, which is associated an $x$-value, $x_0$, assumed lower than that of the less selective graduate school. Admission to this outside option is certain for all students: $p_0(a) = 1$ for all $a \in [0,1]$.

Students have a utility function $u$: $[0,T] \rightarrow \mathbb{R}_+$, with $0 < x_0$ and $x_1 < T$. Students can be of two types regarding their attitudes toward risk: risk-neutral ($N$) or risk-averse ($A$). These students differ in the form of their utility function. Risk-averse students value graduate schools with a higher probability of admission more, so their utility function is concave, and I set $u^A(x) = \sqrt{x}$ for all $x \in [0,T]$. Risk-neutral students do not value these schools more, and thus their utility function is linear; I set $u^N(x) = x$ for all $x \in [0,T]$.

Students can be fee-waiver students ($W$) or fee-paying students ($P$). Fee-paying students pay a fixed amount, $f > 0$, for each of their applications to graduate schools 1 and 2 ($f_1 = f_2 = f$). There are no application fees for the outside option ($f_0 = 0$).

I assume that, for a given ability, admission events to both graduate schools are independent. Writing $E_i$ for the event "The student is admitted to graduate school $i \in \{1,2\}$", we have $E_1 \perp\!\!\!\perp E_2$. This assumption is realistic to the extent that the entrance exams for these schools are distinct competitive entrance exams.

Students have to choose whether to apply to graduate schools 1 and 2; application to the outside option is always assumed. This creates 4 different strategies: $(1,1)$ where they apply to both graduate schools (called strategy 1); $(1,0)$ where they only apply to graduate school 1, the most selective but less likely (called strategy 2); $(0,1)$ where they only apply to graduate school 2, the less selective but more likely (called strategy 3); $(0,0)$ where they do not apply to any of the two graduate schools (called strategy 4).

Students choose the application strategy $(i,k) \in \{(1,1),(1,0),(0,1),(0,0)\}$. They select a the strategy that maximizes their expected utility:

$$\max_{(i,k)\in\{(1,1);(1,0);(0,1);(0,0)\}} U_{(i,k)}$$

Hereafter is the expected utility under the four different application strategies, with $f$ equal to zero for fee-waiver students ($W$):

$$U_{(0,0)} = u(x_0)$$

$$U_{(1,0)} = p_1 u(x_1) + (1-p_1)u(x_0) - f$$

$$U_{(0,1)} = p_2 u(x_2) + (1-p_2)u(x_0) - f$$

$$U_{(1,1)} = p_1 u(x_1) + p_2(1-p_1)u(x_2) + (1-p_1)(1-p_2)u(x_0) - 2f$$

This last expression comes from the fact that students enroll in graduate school 2 only when not admitted to graduate school 1, and to the outside option only if not admitted to graduate school 1 nor 2. As the event of admission to graduate school 1 ($E_1$) and 2 ($E_2$) are independent, $\mathbb{P}(E_2 \cap \overline{E}_1) = \mathbb{P}(E_2)\mathbb{P}(\overline{E}_1) = p_2(1-p_1)$ and $\mathbb{P}(E_0 \cap \overline{E}_1 \cap \overline{E}_2) = \mathbb{P}(\overline{E}_1 \cap \overline{E}_2) = \mathbb{P}(\overline{E}_1)\mathbb{P}(\overline{E}_2) = (1-p_1)(1-p_2)$ (recall that $\mathbb{P}(E_0) = 1$).

**Application strategy of fee waiver students ($W$).** I first observe the best application strategy of fee waiver students ($W$). I will show that both risk-averse ($A$) and risk-neutral ($N$) students apply to both graduate schools. Intuitively, this is because students incur no cost for an extra application, so they mechanically prefer to apply to both graduate schools, which provide them with a higher utility with some positive probability.

**Proposition 1.** Fee waiver students prefer strategy 1 (applying to both graduate schools) over all other strategies, regardless of whether they are risk-averse or risk-neutral.

**Proof of Proposition 1.** See Appendix B.2.1.

**Application strategy of fee-paying students ($P$).** In this paragraph, I consider the optimal application strategy of fee-paying students. I will show that their application strategy depends on (i) the amount of application fees $f$ and (ii) how the ratio of utility $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)}$ compares to the ratio of probabilities $\frac{p_2}{p_1}$. Intuitively, for a low amount of application fee, the optimal strategy is the same as with no application fees, $(1,1)$. As the amount of fees increases, the optimal strategy shifts to either $(1,0)$ or $(0,1)$, depending on the utility to probability ratio. When the fees increase further, the optimal strategy becomes $(0,0)$.

**Proposition 2.**

- If $f < \min((1-p_1)p_2(u(x_2)-u(x_0)), p_1(u(x_1)-u(x_0)) - p_1p_2(u(x_2)-u(x_0)))$, the optimal strategy is the same as without application fees, that is, $(1,1)$

- If $\min((1-p_1)p_2(u(x_2)-u(x_0)), p_1(u(x_1)-u(x_0)) - p_1p_2(u(x_2)-u(x_0))) < f < \max(p_1(u(x_1)-u(x_0)), p_2(u(x_2)-u(x_0)))$:

  - If $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} > \frac{p_2}{p_1}$, the optimal strategy is $(1,0)$
  - If $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} < \frac{p_2}{p_1}$, the optimal strategy is $(0,1)$

- If $\max(p_1(u(x_1)-u(x_0)), p_2(u(x_2)-u(x_0))) < f$, the optimal strategy is $(0,0)$.

**Proof of Proposition 2.** See Appendix B.2.2.

**Differences in application strategy of risk-neutral and risk-averse students ($N$, $A$).** In this section, I examine how the application strategies of risk-neutral ($N$) and risk-averse ($A$) students differ. The main takeaway is that risk-averse students are more frequently opting for the less selective school than are risk-neutral students.

**Proposition 3.**

- Risk-averse students switch from applying to the most selective graduate school only to applying to the less selective graduate school only at lower values of the $\frac{p_2}{p_1}$ ratio;

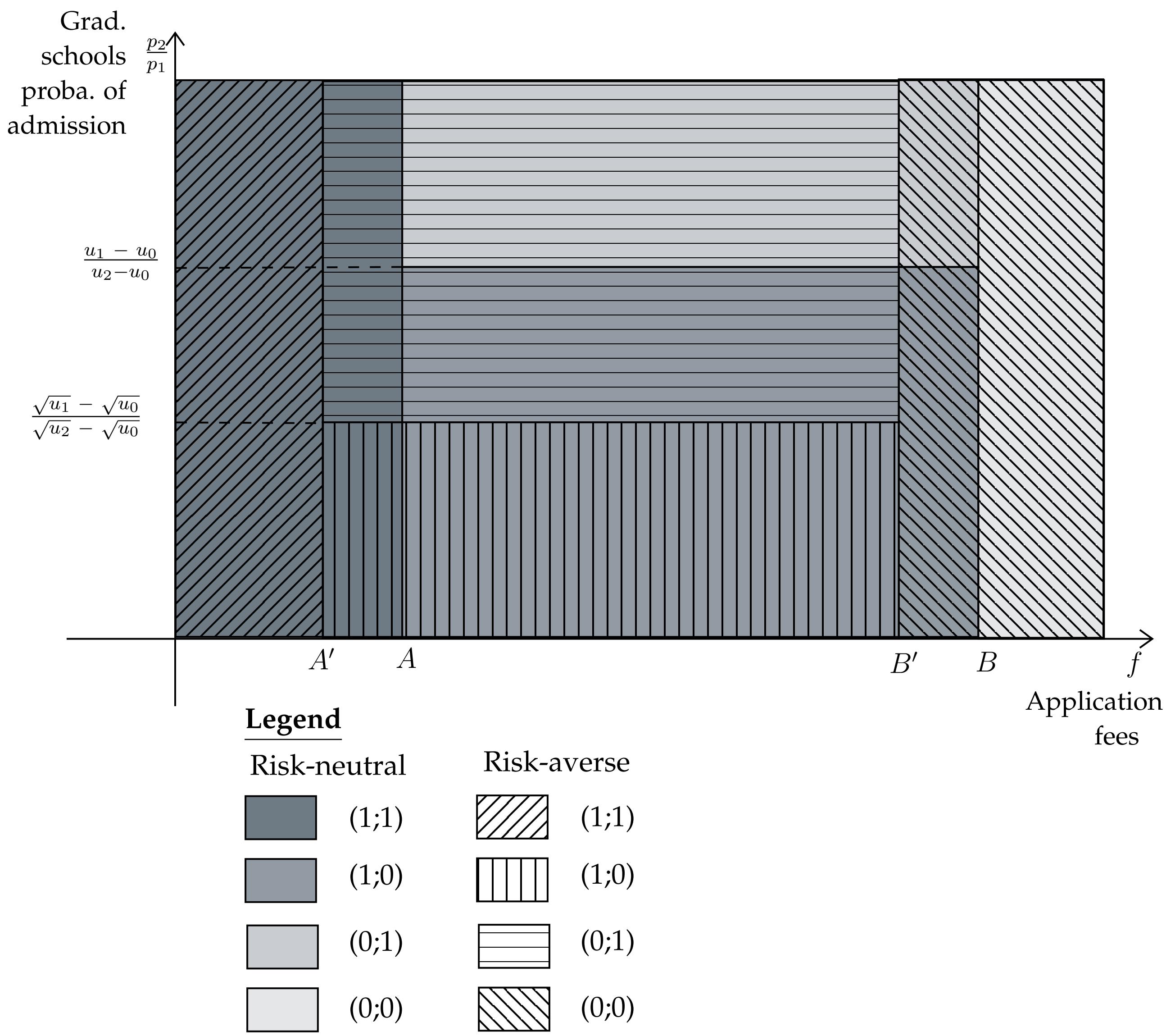
- If all values of $x$ are assumed to be greater than 1, i.e. $x_0 > 1$, we further have:

- Risk-averse students switch from applying to both schools to applying to only one of the two graduate schools at lower amounts of application fees than risk-neutral students;
- Risk-averse students switch from applying to one of the two graduate schools to applying to no graduate school at lower amounts of application fees than risk-neutral students.

**Proof of Proposition 3.** See Appendix B.2.3.

The diagram 3 illustrates the optimal application strategy of risk-neutral (in color) and risk-averse (in patterns) students depending on the amount of application fees $f$ and the ratio $\frac{p_2}{p_1}$, in cases when $x_0 > 1$.

Figure 3: Optimal Application Strategy of Risk-Neutral and Risk-Averse Students




*Notes:* This diagram illustrates the optimal application strategy of risk-neutral (in color) and risk-averse (in patterns) students depending on the amount of application fees $f$ and the ratio of probability of admission to the less selective school $p_2$ to the most selective ones $p_1$ $\frac{p_2}{p_1}$, for cases when the valuation of the outside option, $x_0$ is greater than 1: $x_0 > 1$. Strategy (1,1) means applying to both graduate schools, strategy (1,0) means applying to the most selective graduate school only, strategy (0,1) means applying to the less selective graduate school and strategy (0,0) means applying to no graduate school. Calling $x_1$ the valuation of graduate school 1, the most selective and $x_2$ the valuation of graduate school 2, the less selective, $A' = \min((1-p_1)p_2(\sqrt{x_2} - \sqrt{x_0}), p_1(\sqrt{x_1} - \sqrt{x_0}) - p_1 p_2(\sqrt{x_2} - \sqrt{x_0}))$; $A = \min((1-p_1)p_2(x_2 - x_0), p_1(x_1 - x_0) - p_1 p_2(x_2 - x_0))$; $B' = \max(p_1(\sqrt{x_1} - \sqrt{x_0}), p_2(\sqrt{x_2} - \sqrt{x_0}))$; and $B = \max(p_1(x_1 - x_0), p_2(x_2 - x_0))$.

# 4 Data and descriptive statistics

In this section, I detail the various sources of data used in the analysis. For individual-level data, these sources are matched using an encrypted individual identifier (INE). I retain only those students with a valid student identifier, which allows matching across the different administrative data sources.[14] Subsequently, I present the descriptive statistics of the analysis sample.

**Competitive Entrance Exam Data (SCEI, 2015-2021).** I exploit novel administrative data from the centralized admission process to STEM graduate schools organized by the *Service de Concours Écoles d'Ingénieur* (SCEI) from 2015 to 2021. The data contains students' demographic information (age, gender, social background, geographical origin, fee waiver status, etc.), students' academic information (program, track, class, repeater status), the list of competitive entrance exams that each applicant decided to take – which allows to recover a set of graduate schools to which they have applied, the amount of application fees they had to pay for the entrance exams, their results at the competitive exams (at the written and oral exams), student Rank Ordered List (ROL) of schools, and admission outcomes for each of the five rounds of the admission process.

**Need-Based Grant Application (AGLAE-SIES, 2013-2019).** I supplement the admission process data with need-based grant application data (AGLAE). This data includes student demographic information, parental taxable income, and the composite family needs assessments score based on the number of siblings and distance to the higher education program. It also details whether the student is granted need-based grant status and, if so, the level (*échelon*) of the grant. This data allows us to determine where individuals stand in relation to the eligibility threshold, which is impossible with the SCEI data containing only binary information about whether or not the student is granted the waiver.

[14] Among all applicants to STEM graduate schools over the period under consideration (2015-2021), there is a valid identifier for 74% of all applicants. However, this figure increases to 93% when focusing on French students, who constitute 81 percent of all applicants to STEM graduate schools.

**Enrollment in Higher Education (SISE-SIES, 2015-2021).** I use administrative data on higher education enrollment to track the post-preparatory program pathways of students. These datasets are particularly valuable because they include enrollment in both engineering STEM graduate schools and academic STEM graduate schools (*Écoles Normales Supérieures*, ENS), representing the expected outcomes for STEM prep program students. Additionally, they cover enrollment in university programs and other types of educational programs (business schools or specialized programs), allowing me to track enrollment pathways for 95 to 97 percent of all applicants to STEM graduate schools. This comprehensive coverage enables the examination of completion rates for the initial cohorts in my study (2015-2019).

**Previous Academic Achievement (OCEAN-DEPP, 2010-2020).** To gather information on previous academic achievement, I rely on administrative data on high school and middle school national exam results (*OCEAN-Bac* and *OCEAN-DNB*). In France, these exams are graded on a national scale. This dataset includes information on the GPA obtained in these exams, as well as the grades obtained in each specific subject.

**Tuition Fees of STEM Graduate Schools (CTI, 2015-2023).** There is no administrative data on tuition fees of STEM graduate schools. I web-scraped data from the *Commission des Titres d'Ingénieurs* (CTI) about tuition fees in those schools over the period 2015-2023. The CTI is the committee in charge of granting the accreditation to STEM graduate schools, so these schools have the legal obligation to report information concerning tuition fees and other details accurately.

**Expected Earnings of Graduates.** I gather information on expected earnings of graduates one year after graduation also from CTI for students of STEM graduate schools, and from MESRI-OPEN DATA for expected earnings of university students. These data on university students are available at the major level, so I only retain STEM majors, as STEM prep program students are for the vast majority enrolling in those majors when not gaining admission to STEM graduate schools. Data are available at the program $\times$ cohort level, and further disaggregated by gender for STEM graduate schools. I impute missing values using data from adjacent years and the average growth of earnings over cohorts within a graduate school or university program.[15] Data on STEM graduate school concerns one year after graduation, while data from university programs concerns 18 months after graduation. Both sources display annual gross earnings, including bonuses. Overall, data on expected earnings are available for around 70 percent of my main sample of analysis.

**Sample Restrictions.** My main sample consists of applicants to STEM graduate schools from 2015 to 2021 who also applied for a need-based grant either one year or two years prior to taking the high-stakes entrance exams.[16] I only retain in the main sample individuals whose parental income falls within the range -15 percent to +15 percent of the eligibility threshold for two main reasons: (i) there is a rapid decline in the number of need-based grant applicants not eligible to receive need-based grant status at the fee waiver threshold, and (ii) a second parental income threshold, which qualifies for a higher grant amount, is set at -0.3 relative to parental income compared with the fee waiver threshold. To avoid conflating the effects of waiving the application fee with those of receiving a higher need-based grant amount, I exclude individuals outside this income range. Furthermore, I require that students applied for the need-based grant program for the first time either in the first or second year of the prep program and that they are taking the entrance exams for the first time.[17] This results in a sample of 11,945 individuals applying to STEM graduate schools for the first time between 2015 and 2021 (see Table 1).

**Descriptive Statistics.** Table 1 presents descriptive statistics for the sample used in the regression discontinuity analysis, comprising 11,945 students, whereas Table B2 in the Appendix details the same statistics for the entire cohort of preparatory program students, including 245,559 individuals. Within the RD sample, 57 percent of the students are beneficiaries of fee waivers as against 26 percent in the full sample. As expected, fee waiver applicants, compared

[15]For university programs where fewer than 30 respondents were observed, the average amount observed at the national level for students specializing in that major was applied. Unfortunately, this concerns about half of the university programs, but only 20 to 30 students enrolled in university programs within my sample.

[16]For more details, see the Empirical Strategy Section of the paper.

[17]I do so because repeaters, having been in higher education for three years, are less likely to apply for a need-based grant when not eligible, suggesting a potential for more selection bias in this sample. It could also be that the probability of repeating varies at the application fee waiver threshold, in practice I observe that this is not the case (see Panel A. of Table 6).

to their fee-paying counterparts just above the eligibility threshold, hail from families with lower annual taxable incomes ($45,000 versus $50,000) and exhibit marginally higher family needs assessment scores (4.4 compared to 4.17). Other demographic and academic characteristics display a high degree of balance between fee waiver and non-fee waiver applicants within this restricted RD sample. This is in sharp contrast to the descriptive statistics of the full sample (Table B2), where fee waiver applicants are from lower socioeconomic backgrounds (with an average SES index of 118 versus 145, and 28% of their fathers coming from high SES backgrounds, as opposed to 69% of fee-paying applicants),[18] demonstrate lower academic achievements (43% achieving the high school graduation exam with the highest honors compared to 51% of fee-paying applicants), and are less frequently from Paris (4% versus 7%) or the Parisian region (16% versus 19%).

# 5 Empirical Strategy

I identify the effect of having to pay application fee on STEM graduate schools application, admission and enrollment outcomes using a regression discontinuity design at the application fee waiver threshold. Conducting a basic OLS regression of STEM school admission on fee waiver status would confound the effect of the fee waiver with that of parental income, as the fee waiver is a function of parental income. On average, applicants who benefit from the fee waiver experience less favorable admission outcomes. This trend is likely attributable to factors unrelated to the fee waiver itself, as this group predominantly consists of low-income students. Moreover, not all eligible individuals apply to need-based grant that provides the fee-waiver, and the decision to apply could be correlated to unobservable factors relevant for the outcome of interest, for instance the number of application foreseen.

Given that the income thresholds for fee waivers are externally established and assuming that the information provided to the national student service agency is not subject to manipulation by applicants, the fee waiver can be regarded as locally randomly allocated. This means that the causal impact of the application fees can be obtained by comparing the outcomes of

[18] For the Socioeconomic Status (SES) Index, I employ the index developed by the Statistical Service of the Ministry of Education (DEPP), known as the IPS (*Indice de Position Sociale*) Index. This index is designed to consolidate the occupational categories of both parents, each in 44 categories, into a single continuous metric.

Table 1: Descriptive Statistics of the RDD Sample

| | Sample | | |
|---|---|---|---|
| | All students (1) | Non fee waiver students (2) | Fee waiver students (3) |
| *Panel A. Demographic Characteristics* | | | |
| Need-based scholarship holder | 0.57 | 0.00 | 1.00 |
| Parents' taxable income | 47,318 | 49,787 | 45,465 |
| Family needs assessment score | 4.30 | 4.17 | 4.40 |
| Female student | 0.32 | 0.32 | 0.32 |
| From Paris | 0.02 | 0.02 | 0.02 |
| From Parisian area (outside Paris) | 0.12 | 0.12 | 0.13 |
| SES index | 133.55 | 136.02 | 131.69 |
| Father High SES | 0.44 | 0.47 | 0.41 |
| Father Medium High SES | 0.17 | 0.17 | 0.16 |
| Father Medium Low SES | 0.24 | 0.22 | 0.25 |
| Father Low SES | 0.11 | 0.10 | 0.12 |
| Mother High SES | 0.34 | 0.37 | 0.32 |
| Mother Medium High SES | 0.19 | 0.20 | 0.18 |
| Mother Medium Low SES | 0.34 | 0.32 | 0.35 |
| Mother Low SES | 0.07 | 0.06 | 0.08 |
| *Panel B. Previous Academic Achievement* | | | |
| *Baccalauréat* GPA | 15.72 | 15.67 | 15.76 |
| Highest honors at the *Baccalauréat* | 0.51 | 0.49 | 0.52 |
| Top 10% of students at the *Baccalauréat* | 0.36 | 0.35 | 0.37 |
| *Panel C. Prep Program Characteristics* | | | |
| Enrolled in star class (top track) | 0.25 | 0.24 | 0.25 |
| Prep program in Paris | 0.09 | 0.08 | 0.09 |
| Prep program in Parisian area (outside Paris) | 0.08 | 0.08 | 0.09 |
| Track 1 (MP) | 0.26 | 0.25 | 0.26 |
| Track 2 (PC) | 0.20 | 0.20 | 0.20 |
| Track 3 (PSI) | 0.22 | 0.22 | 0.22 |
| Track 4 (PT) | 0.11 | 0.12 | 0.11 |
| Track 5 (BCPST) | 0.14 | 0.14 | 0.14 |
| **Number of students** | 11,945 | 5,123 | 6,822 |

*Notes:* This table presents the descriptive statistics for students included in the regression discontinuity analysis. Specifically, it includes students who took high-stakes entrance exams from 2015 to 2021, applied for need-based grants between 2013 and 2019, and were within a [-0.15; 0.15] relative income distance from the fee-waiver threshold. The statistics are provided for all students in Column 1, and the sample is subsequently divided between fee-waiver recipients in Column 2 and non-fee-waiver students in Column 3. Socioeconomic Status (SES) is categorized according to the classification system of the Ministry of National Education, using either a four-category scheme or the Index of Parental Socioeconomic Status (IPS), which aggregates both parents' occupations into a single metric. For comparative purposes, Table B2 in the Appendix presents these descriptive statistics for the entire sample of prep program students (N=245,559).

applicants just above the income threshold (treatment group) and just below it (control group). For reasons of statistical power, I aggregate all income thresholds generated by the different composite scores from the family needs assessment. This is done by calculating a relative income distance to the fee waiver threshold, following the methodology proposed by Fack and Grenet (2015) in the evaluation of the impact of need-based grants in France. This also provides results that are applicable to a broader population than those based on a single, unique threshold, partly limiting the drawbacks of regression discontinuity results being LATE estimates: individuals very close to the eligibility threshold ([-3,+3] in relative parental income) have an average parental income of 46,900 euros with a standard deviation of 10,500 euros.

Let $z$ denote parental income, $s$ the family needs assessment score, and $\bar{z}(s)$ the income threshold to qualify for the fee waiver for an individual with a family needs assessment score $s$. Assuming that, in the absence of the fee waiver, the outcome of interest is a smooth function of the running variable (parental income), the causal effect of having to pay the application fees, compared to not having to pay the fees, on admission and enrollment outcomes $y$ is identified by:

$$\beta^{\text{RD}} = \lim_{z \to \bar{z}(s)^{+}} E(y|z,s) - \lim_{z \to \bar{z}(s)^{-}} E(y|z,s) \tag{1}$$

The specification for estimating the impact of having to pay application fees on outcome $y$ is as followed:

$$y_i = \beta_0 + \beta_1 \mathbb{1}(z_i \geq \bar{z}(s_i)) + \beta_2 f(z_i) + \epsilon_i \tag{2}$$

With $\mathbb{1}(z_i \geq \bar{z}(s_i))$ being a dummy variable taking the value 1 if individual $i$ has parental income $z_i$ falling above the income threshold for their family needs assessment score, $\bar{z}(s_i)$, and $f(z_i)$ a function that controls for the running variable — in this case, parental income.

Following Cattaneo et al. (2019)'s guidelines, the coefficient of interest, $\beta_1$ is estimated non-parametrically with local linear regressions fitted on both sides of the threshold. A triangular kernel is used to give more weight to observations near the threshold. I use Calonico et al. (2014) procedure to select the optimal bandwidth, which varies for each outcome. I report bias-corrected point estimates and robust standard errors, using the robust bias-correction procedure described in Calonico et al. (2014). I cluster standard errors are the track $\times$ program $\times cohort$ level. In Table J10, I check that my main result concerning admission chances to STEM graduate schools is robust to changing bandwidth size or using a higher-order polynomial.

**Intent-to-Treat Estimates.** The coefficient of interest of Equation 2, $\beta_1$ represents an intent-to-treat estimate as I consider the effect of located above the application fee threshold versus below, regardless of whether the applicants actually benefit from the application fee waiver or not. In practice, the fee waiver threshold does not create a perfectly sharp discontinuity for two reasons: first, some applications are either withdrawn or dismissed by the student service agency for failing to satisfy all administrative or academic prerequisites; second, in order to recover as many individuals as possible, I pool two years of applications to the need-based grant program (more details on this below), which means that I include certain individuals who were eligible during the first year in the preparatory program but not in the second year, due to reasons such as a rise in parental income or a sibling no longer being part of the parents taxable household.

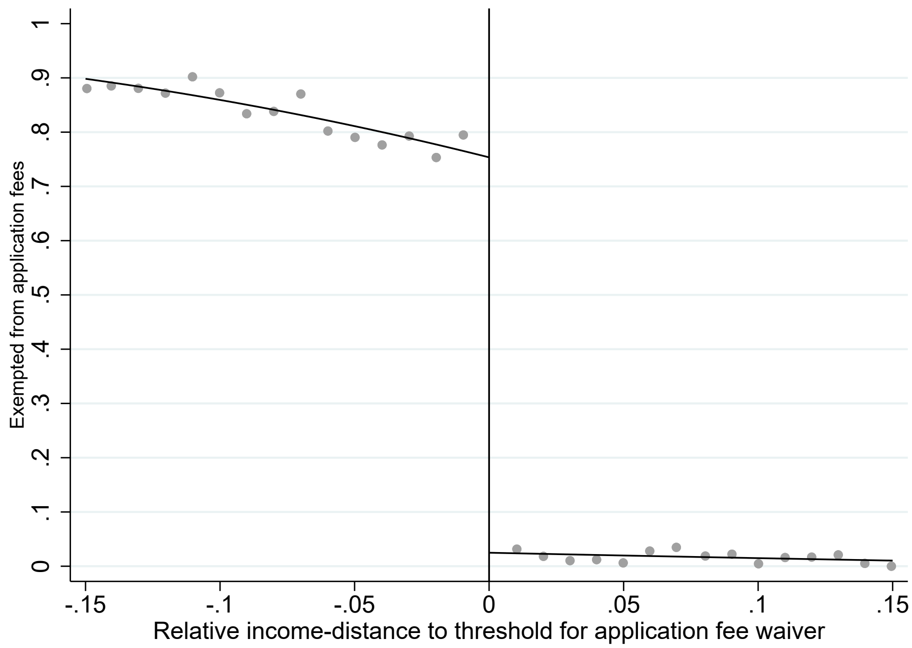
**First Stage.** For the identification strategy to be able to identify the impact of application fees, it is essential that the likelihood of receiving an application fee waiver exhibits a clear discontinuity at the exemption threshold. The first stage, meaning the effect of being above the eligibility threshold on the likelihood of benefiting from an application fee waiver is estimated as follows:

$$D_i = \alpha_0 + \alpha_1 \mathbb{1}(z_i \geq \bar{z}(s_i)) + \alpha_2 f(z_i) + \epsilon_i \tag{3}$$

With $D_i$ being a dummy indicator taking the value 1 if individuals benefit from a fee waiver.

Figure 4 shows an important discontinuity in the likelihood of receiving a fee waiver exactly at the threshold, with an around 70 percent reduction in the probability of benefiting from fee exemption at this threshold.

Figure 4: First Stage of the Regression Discontinuity: Probability To Be Fee Exempted




*Notes:* The circles on the graph depict the probability to be fee exempted, as a function of the distance between applicants' parental income and the application fee waiver threshold. The solid lines on the graph represent the estimated values obtained from a second-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver. The Regression Discontinuity Design is not sharp for two reasons: firstly, some applications are either withdrawn or dismissed by the student service agency for failing to satisfy all administrative or academic prerequisites; secondly, by pooling two years of applications (and retaining the later one), I include certain individuals who were eligible during the first year in the preparatory program but not in the second year and didn't apply to the need-based grant program, due to reasons such as a rise in parental income or a sibling no longer being part of the parents taxable household.

**2SLS Estimates.** The 2SLS estimation procedure estimates the impact of application fees with the following regression:

$$y_i = \gamma_0 + \gamma_1 \hat{D}_i + \gamma_2 f(z_i) + \epsilon_i \tag{4}$$

With $\hat{D}_i$ representing the prediction from Equation 3, $\hat{\gamma}_1$ denotes the 2SLS estimates of the causal effect of having to pay application fees for compliers (i.e., those who do not pay application fees when below the threshold and do pay when above it). This estimation hinges on the assumption of (i) the pertinence of the instrument and (ii) the exogeneity of the instrument. Pertinence is evidenced by a strong first stage, approximately 0.7. The threshold is administered exogenously, making manipulation challenging given that the administration in charge requires official documentation, such as parental tax returns (see below for further discussion on the validity of the empirical strategy). Another requirement is the absence of defiers, defined as individuals who would benefit from the fee waiver if above the eligibility threshold but not below. It is highly unlikely that there are defiers in this setting. This makes the eligibility threshold a good instrument for benefiting from the fee waiver.

Table C3 in the Appendix displays the characteristics of compliers, always takers, and never takers using the procedure described in Abadie (2002), Abadie (2003), and Angrist et al. (2023). Overall, the characteristics of compliers, always takers, and never takers are quite similar. However, compliers show marginally better previous academic achievement; approximately 52 percent of them obtained the high school graduation exam with highest honors compared to 48 percent of always takers and 44 percent of never takers. Untreated compliers are similar to treated compliers, consistent with the balance of observable characteristics (see Table 2 and the discussion below). The primary exception is the parents' socioeconomic background, with treated compliers generally coming from lower socioeconomic statuses. This trend aligns with the design of the treatment, which is based on parental income, resulting mechanically in higher socioeconomic statuses among the untreated.

In the remainder of the article, all graphs present the reduced form, whereby the observed discontinuity at the threshold illustrates the intent-to-treat estimates ($\hat{\beta}_1$, derived from Equation 2). Conversely, the table results represent the 2SLS estimates ($\hat{\gamma}_1$, derived from Equation 4).

Given that the first stage is approximately 0.7, 2SLS estimates are scaled up by a factor of 1.4 times the ITT estimates.[19]

## 5.1 Validity of the Empirical Strategy

A key condition for the RD strategy to produce unbiased estimation of the treatment under consideration is the non-manipulation of the running variable.

**Density of the Running Variable Around the Threshold.** Unfortunately, the criteria for eligibility for need-based grants have remained unchanged throughout my period of study.[20] This creates a situation where some individuals who do not meet the eligibility criteria might decide not to apply for the need-based grant. Without their application, I cannot observe their position in relation to the application fee waiver cutoff, as I have no reliable information on parental income and the composite family needs assessment score. This may create a noticeable discontinuity in density at the threshold and a potential for selection bias around that threshold. However, the eligibility calculation is rather intricate, factoring in taxable parental income from two years prior, the total number of siblings, the number of siblings in higher education — which can vary across years — and the distance to the higher education program — which may vary among the different programs applied to. Given the significant advantages associated with obtaining need-based grant status, it is anticipated that many individuals close to the eligibility threshold would apply to the program anyway. To recover as many individuals as possible around the application fee waiver threshold, I pool two years of application to the need-based grant program. An individual is considered in the analysis if they applied for a need-based grant during the senior year of high school for the first in prep program and/or during the first year in prep program for the second year in the prep programs.[21] I then retain only the latest observation for each individual. I do so because ineligible individuals are unlikely to apply every year, as the application process requires filing forms and providing official documents, but

[19] In practice, the optimal bandwidth as recommended by Cattaneo et al. (2019) varies between ITT and 2SLS, resulting in scaling factors that are not consistently 1.4 across all estimates.

[20] The income thresholds were set unchanged for the period 2011-2022, and have not been adjusted in line with inflation or income growth, leading to a slight reduction in the number of eligible individuals.

[21] Individuals have to apply to the need based grant program during January and April of each academic year, for the following academic year. See Timeline C3 in the Appendix for details of the need-based grant application and STEM graduate school application calendar.

they are likely to apply at least once to test for eligibility, particularly when entering higher education for the first year in prep program. This creates a fuzzy regression discontinuity design (see more details on the estimation strategy above). I also impose the condition that individuals must be first-time applicants to the need-based grant program, whether applying for the first or second year in the prep program, thereby excluding the few individuals who change path. I also focus on individuals taking the high-stakes entrance exams for the first time and thus excluding repeaters.[22] Figure 5 shows the density of my main sample of analysis (N=11,945), which is sharply decreasing at the threshold but not significantly discontinuous. Table D4 in the Appendix displays the RD density test (Cattaneo et al., 2018) for different bandwidths and Cumulative distribution function (CDF). In none of these specifications does the test reveal any significant discontinuity in density around the eligibility threshold.

Figure 5: Density Test For the Main Sample of Analysis


*Notes:* The graph illustrates the density of the running variable, in the vicinity of the application fee waiver threshold for the main sample of analysis. This main sample consists of pooled data from two consecutive years of applications to the need-based grant program. If an individual applied only in the first year of the preparatory program, that application is included in the sample. However, if an individual applied in both years, only the second-year application is included. This approach is adopted to maximize the number of individuals included in the right part of the distribution. The x-axis represents relative income distance to the fee waiver threshold, while the y-axis represents the density of observations.

[22] I do so because repeaters, having been in higher education for three years, are less likely to apply for a need-based grant when not eligible, suggesting a potential for more selection bias in this sample. It could also be that the probability of repeating varies at the application fee waiver threshold, in practice I observe that this is not the case (see Panel A. of Table 6).

**Balance of Observable Characteristics.** In Table 2, I present the balance of observable characteristics. Column 2 details a simple linear regression analysis, where each demographic characteristic is regressed on the probability of admission to at least one STEM graduate program, my main outcome of interest. The analysis reveals that most demographic characteristics and prior achievements significantly contribute to explaining admission outcomes. For instance, an increase in parents' annual income by 1,000 euros is associated with an increase in admission probability by 0.3 percentage points (p.p.), equivalent to a 0.4 percent increase from a baseline admission rate of approximately 80 percent. Scoring among the top 10 percent of students at the high school graduation exams increases this probability by 15 p.p. Reassuringly, Column 3 of Table 2 indicates the absence of significant discontinuities in the observable characteristics at the threshold. The only significant discontinuity is observed among Track 3 students, who are less numerous on the right side of the threshold.[23] In particular, no significant discontinuities are observed in prior educational achievements, as measured by grades obtained in the national high school examination (*Baccalauréat*), whether in terms of GPA, likelihood of being in the top 10 percent of high achievers, or any individual grade. Concerns about selection bias around the threshold, particularly that less aware applicants might apply despite being ineligible, would likely manifest through patterns in previous academic achievement. The absence of such patterns is reassuring and suggests that this form of selection bias does not compromise the findings. Figures H8 in the Appendix depict the distribution of observable characteristics around the regression discontinuity (RD) threshold. Consistent with the findings presented in Table 2, there are no significant discontinuities or jumps in any of the characteristics at the threshold. Additionally, the F-Test of joint significance (panel D of Table 2) also highlights the inability to reject the null hypothesis, which suggests that the discontinuity gaps in observable characteristics are collectively equivalent to zero.

**Same Threshold Used for Multiple Treatments.** The fee waiver threshold depends on the need-based grant status. Obtaining this status affects more than just eligibility for an application fee waiver.

[23]This could be by chance, as I test many coefficients, but I run a robustness tests of the main results regarding admission outcomes to STEM graduate schools including track fixed effects (see Table K11 in the Appendix). The findings are remarkably consistent across both specifications.

## Table 2: Balance of Applicants' Baseline Characteristics

| | Baseline mean (1) | Receive Admission Offer (2) | RD_Estimate (3) |
|---|---|---|---|
| *Panel A. Tracks* | | | |
| Track 1 (*MP*) | 0.26 | 0.011 | 0.045 |
| | | (0.009) | (0.057) |
| Track 2 (*PC*) | 0.20 | 0.044*** | 0.055 |
| | | (0.009) | (0.058) |
| Track 3 (*PSI*) | 0.22 | 0.089*** | -0.089* |
| | | (0.009) | (0.046) |
| Track 4 (*PT*) | 0.11 | 0.015 | -0.002 |
| | | (0.012) | (0.038) |
| Track 5 (*BCPST*) | 0.14 | -0.124*** | -0.017 |
| | | (0.011) | (0.047) |
| *Panel B. Demographic Characteristics* | | | |
| Parent's taxable income (in thousand euros) | 45.41 | 0.003*** | 0.745 |
| | | (0.000) | (1.119) |
| Family needs assessment score | 4.41 | 0.011*** | 0.208 |
| | | (0.001) | (0.304) |
| Female | 0.32 | -0.024*** | -0.004 |
| | | (0.008) | (0.062) |
| French Nationality | 1.00 | -0.037 | -0.007 |
| | | (0.049) | (0.010) |
| Student with a Disability | 0.02 | -0.014 | 0.008 |
| | | (0.026) | (0.019) |
| SES index | 131.71 | 0.001*** | 0.914 |
| | | (0.000) | (3.648) |
| Father High SES | 0.41 | 0.061*** | 0.038 |
| | | (0.007) | (0.057) |
| Mother High SES | 0.32 | 0.037*** | 0.070 |
| | | (0.008) | (0.051) |
| From Parisian area | 0.15 | 0.039*** | -0.028 |
| | | (0.011) | (0.041) |
| Prep program in Parisian area | 0.18 | 0.067*** | -0.032 |
| | | (0.010) | (0.045) |
| *Panel C. Previous Academic Achievement* | | | |
| *Baccalauréat* GPA | 15.76 | 0.058*** | -0.124 |
| | | (0.002) | (0.211) |
| Highest honors at the *Baccalauréat* | 0.52 | 0.181*** | -0.028 |
| | | (0.007) | (0.058) |
| *Baccalauréat* top 10 percent of students | 0.37 | 0.150*** | 0.021 |
| | | (0.008) | (0.058) |
| *Baccalauréat* math. grade | 16.27 | 0.036*** | -0.018 |
| | | (0.001) | (0.289) |
| *Baccalauréat* physics & chemistry grade | 16.00 | 0.043*** | 0.150 |
| | | (0.001) | (0.279) |
| *Baccalauréat* engineering science grade | 15.81 | 0.033*** | -0.584 |
| | | (0.003) | (0.793) |
| *Baccalauréat* French grade | 13.39 | 0.018*** | -0.340 |
| | | (0.001) | (0.301) |
| *Baccalauréat* language grade | 15.33 | 0.022*** | -0.489 |
| | | (0.001) | (0.347) |
| *Panel D. All Baseline Characteristics Jointly* | | | |
| *F-Stat* | | | 1.337 |
| *P-value* | | | 0.117 |
| Number of obs. | | | 11,945 |

*Notes:* This table presents the balance of applicants' baseline characteristics at the application fee waiver threshold. Column 1 shows the baseline mean of the characteristics considered for applicants below the fee waiver eligibility threshold. Column 2 displays the coefficients from a simple linear regression, with the characteristics as independent variables and the outcome of interest (receiving admission to STEM graduate schools) as the dependent variable. Column 3 displays nonparametric regression discontinuity estimates, based on Calonico et al. (2017), to compare the characteristics of applicants at the application fee waiver threshold. Each coefficient is derived from a separate regression, where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are clustered at the *track* $\times$ *program* $\times$ *cohort* level. Robust p-values are indicated in parentheses. Panel A, Panel B, and Panel C each assess different aspects of applicants baseline characteristics at the fee waiver threshold, including track, demographic characteristics, and previous academic achievement.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

One notable advantage of determining fee waiver eligibility through an external program (the need-based grant application) is the transparency and reliability of the application process. Additionally, most students are incentivized to apply due to the numerous benefits of obtaining need-based grant status. This contrasts with a scenario in which a separate application for the application fee waiver might increase demand among students planning to apply to numerous STEM graduate schools, potentially leading to greater bunching and selection around the fee waiver eligibility threshold. Nevertheless, a drawback of this system is that it is more challenging to identify the effect of the application fee alone.

First, students falling below the need-based grant threshold are exempted from paying tuition fees at public institutions and, from 2016 onwards, receive a grant of around €1,000 per year over my period of study. Tuition fees in prep programs are set at the official level for public university undergraduate programs, ranging from 170 to 185 euros per academic year, as specified in official documentation. The exemption from tuition fees, along with the grant, could help grant-eligible students to remain in the prep program and take high-stakes entrance exams more frequently. If that were to happen, the student population to the right of the fee waiver threshold would be more selected, comprising those able to remain in the prep program despite not benefiting from the grant and tuition fee waiver. However, this does not seem to be the case based on observable characteristics (Table 2). In my main sample, I include only those who take high-stakes entrance exams. However, I analyze the full sample of first-year prep program students to ensure that the probability of taking these exams does not exhibit discontinuity at the threshold. This discrepancy could arise either from differential dropout rates among students or from their decision not to take the exams despite completing the prep program course. As observed in Table L12, 77 percent of first-year prep program students falling below the need-based grant threshold are observed in the main sample of exam takers, with no significant discontinuity detected at the threshold (the coefficient on the probability of being observed in the exam takers sample is exactly 0 at the threshold). Furthermore, I confirm that my main results regarding admission outcomes remain robust when using the full sample of first-year prep program students (see Table M13). Although the results are less precisely estimated than those for exam-taking students, all coefficients are negative and of a similar order of magnitude of my main estimates.

Another factor that varies at the application fee waiver threshold is the requirement to pay tuition fees in public STEM graduate schools.[24] Private schools, which are much more expensive, do not waive tuition fees for low-income students. To ensure that my results regarding application behavior and admission outcomes are not influenced by anticipated tuition fees, I examine the average amount of theoretical tuition fees (i.e., tuition fees for those who are required to pay them, or "sticker price") around the application fee waiver threshold for (i) graduate schools applied to and (ii) graduate schools of admission. Table P16 shows that candidates paying application fees tend to apply to graduate schools with slightly lower tuition fees (Column 1). However, this pattern doesn't persist once we only consider public STEM graduate schools, those for which the amount of tuition paid also varies at the threshold (Column 2): fee waiver and fee-paying students apply to equally expensive public graduate schools on average. No significant difference is observed regarding the tuition fees of the STEM graduate schools to which applicants receive admission offers, both for all graduate schools (Column 3) and public ones (Column 4). This suggests that students do not heavily consider tuition fees when making their application choices. This rather myopic behavior among students could be explained by: (i) these individuals being at the margin of the fee waiver, so some may not be granted the waiver the following year due to a rise in parental income (around 30 percent of them lose the waiver from one year to the next); (ii) the low variance in fees at public STEM graduate schools, typically set at €601 per year for most programs and between €1,850 to €3,500 for a selected few (see Figure I9(a)); and (iii) the most expensive public programs generally extending partial tuition fee exemptions to individuals close to the waiver eligibility threshold.[25]

I will present the robustness of the results controlling for the average amount of tuition fees of the application set (Table Q17) and discuss this issue in much more detail in the discussion section of the paper.

[24]Figure I9 illustrates the distribution of tuition fees for both public and private STEM graduate schools. See Institutional Background Section for more details on public and private STEM graduate schools.

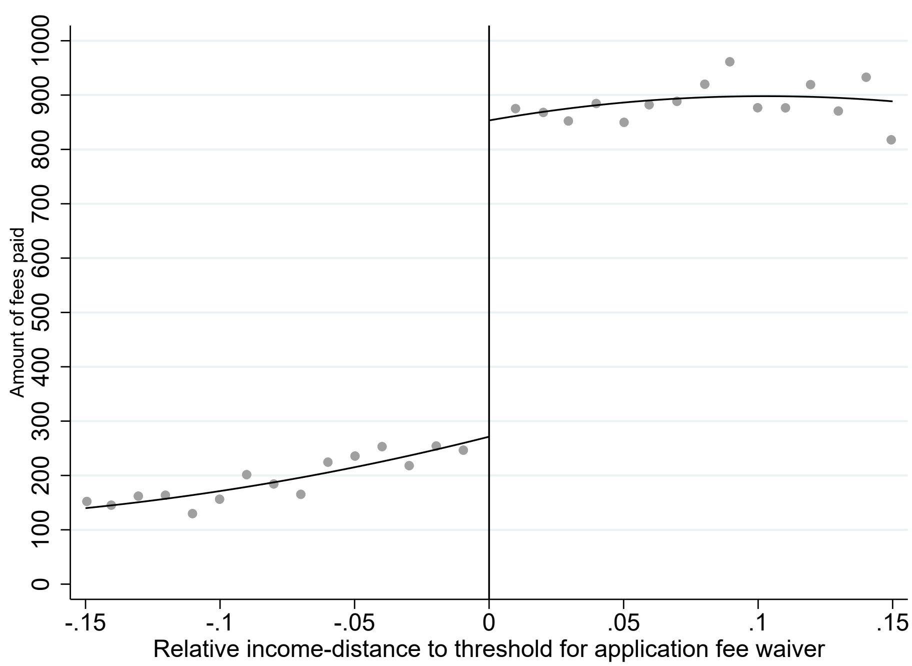
[25]Examples of public graduate schools granting these extra exemptions include *ESPCI*, *IMT Atlantique*, *IMT Lille Douai*, *IMT Mines d'Alès*, *Mines d'Albi*, *Mines de Paris*, *Mines Saint-Étienne*, *Télécom ParisTech*, *Télécom SudParis*, etc.

# 6 Results

In this section, I present the main results of the impact of application fees on application behavior, admission probability, and enrollment outcomes, followed by robustness tests, as well as some heterogeneity results and results regarding the different impact of school-specific application fees versus common application fees to several graduate schools.

**Amount of Application Fees Paid.** I first examine if there is a significant jump in the amount of application fees paid at the application fee waiver threshold. Figure 6 illustrates the reduced-form effect of application fees at the exemption threshold, revealing a marked increase of approximately 600 euros. The Two-Stage Least Squares (2SLS) regression discontinuity estimates, as presented in Table E5, further substantiate this finding by showing that, on average, students paying application fees pay 820 euros more than their fee-waiver counterparts. This difference ranges from around 600 to 1,000 euros, depending on the different STEM prep program track (all amounts in 2021 euros).

Figure 6: Amount of Application Fees Paid for Entrance Exams to Elite STEM Schools

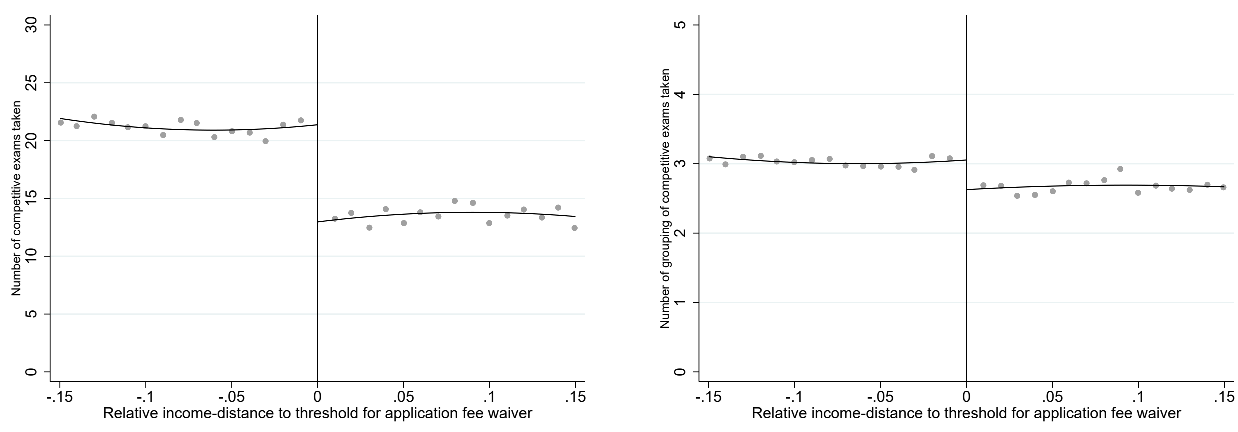



*Notes:* The circles on the graph depict the amount of application fees paid, as a function of the distance between applicants' parental income and the application fee waiver threshold. The solid lines on the graph represent the estimated values obtained from a second-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver.

## 6.1 On Application Behavior

Does the requirement of paying application fees lead to a decrease in the number of entrance exams attempted by candidates? Figure 7 indicates that, on average, candidates required to pay application fees attempt fewer entrance exams (Panel (a)) and fewer clusters of entrance exams (Panel (b)) compared to those who are exempted from the application fees. Specifically, fee-paying candidates attempt, on average, 12.6 fewer entrance exams than fee-waiver candidates (Column 2 of Table 3), which corresponds to a 55 percent reduction in the total number of entrance exams attempted, considering a baseline number of exams attempted by fee-waiver students to be 22.8.

Figure 7: Impact of Application Fees on Application Behavior




(a) Number of Entrance Exams Taken

(b) Number of Grouping of Exams Taken

*Notes:* The circles on the graph represent the number of exams taken (Panel a) and the number of groupings of exams taken (Panel b), as a function of the distance between applicants' parental income and the application fee waiver threshold. A cluster of exams refers to schools that have common entrance examinations. The solid lines on the graph represent the estimated values obtained from a second-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver.

To how many graduate schools and graduate programs does this reduction of entrance exams undertaken by fee-paying candidates correspond?[26] On average, candidates paying fees apply to 23 fewer graduate schools (Column 3 of Table 3) and 43 fewer programs (Column 4 of the same table), representing an around 30 percent reduction for both.

Does this mean that candidates with fee waivers have to take significantly more tests than fee-paying candidates? Column 1 of Table 3 indicates that, on average, fee-paying candidates apply to 0.49 fewer clusters of exams (a 16 percent reduction), suggesting that fee-paying can-

[26] Entrance exams can lead to up to 33 different STEM graduate schools and 111 distinct graduate programs, with a program defined as a specific specialty within a graduate school, such as 'computer science'.

didates take slightly fewer tests, but the difference is not substantial. A single cluster of exams typically includes between 4 to 7 written tests and 4 to 7 oral tests (see Institutional Background section), which means that, on average, fee-paying candidates take 2 to 4 fewer written and 2 to 4 fewer oral exams.

Table 3: Number of Application Sent

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Number of Exam Clusters Taken | Number of Entrance Exams Taken | Number of STEM Graduate Schools Applied To | Number of STEM Graduate Programs Applied To |
| Baseline mean (fee-waiver students) | 3.12 | 22.78 | 79.47 | 146.17 |
| Baseline RD estimate | -0.49*** | -12.57*** | -23.00*** | -43.45*** |
| | (0.17) | (1.27) | (3.51) | (8.34) |
| Robust 95% CI | [-0.81 ; -0.17] | [-15.07 ; -10.08] | [-29.87 ; -16.13] | [-59.79 ; -27.11] |
| Obs. used in estimation | 3,543 | 4,709 | 3,665 | 3,453 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 11,945 |

*Notes:* The table displays the estimated discontinuities in the number of applications sent at the fee-waiver eligibility threshold. Column 1 presents the number of clusters of entrance exams applied to, Column 2 shows the number of individual entrance exams applied to, Column 3 details the number of STEM graduate schools applied to (inclusive of all those accessible through the entrance exams), and Column 4 outlines the number of STEM graduate programs applied to, defined as a specialty within a STEM graduate school. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

What are the applications eliminated by candidates who have to pay application fees? Table 4 shows the change in the selectivity of entrance exams attempted.[27] Candidates paying fees apply to exams that are, on average, equally selective but reduce the range of selectivity of the exams they attempt by 2.3 points (a 19 percent reduction). This range is defined as the difference between the most selective exam taken and the least selective exam taken by the candidate. This is explained by the fact that they increase the selectivity of the least selective exam they attempt (reducing their safety choices) and decrease the selectivity of the most selective (reduc-

[27] The selectivity of entrance exams is defined based on the average percentile rank at the high school graduation exam of individuals attempting the exam.

ing their ambitious choices). These results are consistent with Pallais (2015), which showed that application fees reduce the variance in selectivity of the institutions to which students apply.

Table 4: Selectivity of Entrance Exams Attempted

| | (1) Average Selectivity | (2) Range of Selectivity | (3) Minimum Selectivity | (4) Maximum Selectivity |
|---|---|---|---|---|
| Baseline mean (fee-waiver students) | 77.82 | 12.10 | 71.77 | 83.86 |
| Baseline RD estimate | 0.35 | -2.36*** | 1.42 | -0.93 |
| | (0.75) | (0.74) | (0.94) | (0.63) |
| Robust 95% CI | [-1.11 ; 1.82] | [-3.80 ; -0.91] | [-0.42 ; 3.26] | [-2.16 ; 0.31] |
| Obs. used in estimation | 3,566 | 3,358 | 3,437 | 3,667 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 11,945 |

*Notes:* The table displays the estimated discontinuities in selectivity of exams attempted (range of selectivity, minimum selectivity and maximum selectivity), around the application fee waiver threshold. Selectivity of exams is defined with the average percentile rank at high school graduation exams of students attempting these exams. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

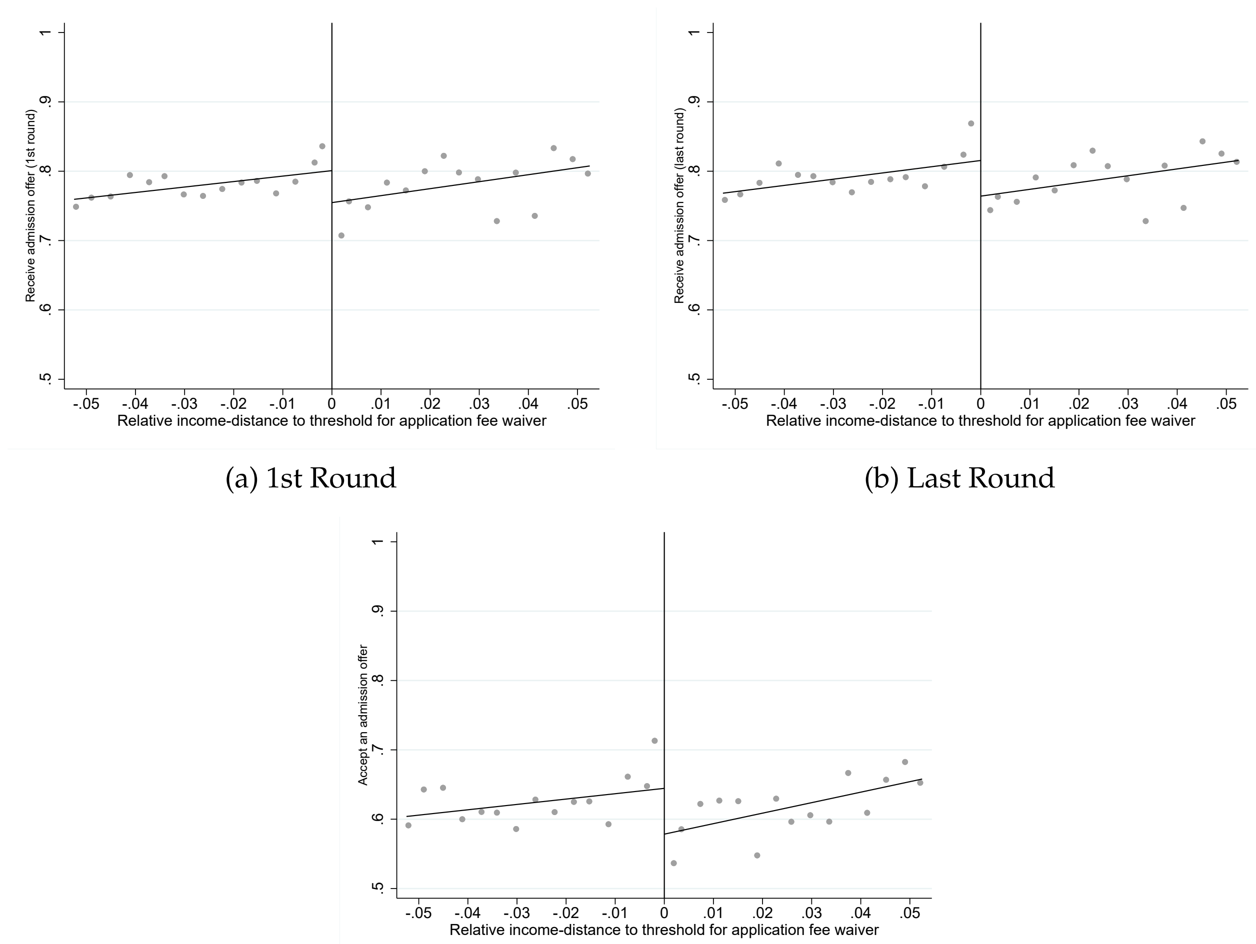
Overall, these results suggest that having to pay application fees leads to a substantial reduction in the number of entrance exams undertaken, and in particular, reduces the diversity of applications undertaken in terms of selectivity.

## 6.2 On Admission Outcomes

Does taking fewer exams by students who pay application fees result in unfavorable admission outcomes? In other words, is this situation costly for these students? It is possible that students are proficient in selectively targeting the exams they opt to take; having dedicated significant time in preparatory programs, they are well-aware of their capabilities and receive guidance from their instructors. Hence, it is conceivable that students paying application fees are adept at targeting the entrance exams of schools to which they would have been admitted regardless of the number of exams taken, making the reduced number of exams inconsequential for them.

Figure 8 and Table 5 show that taking fewer exams indeed has a detrimental effect on admission probability for these individuals. Fee-paying students less frequently receive an admission offer from at least one STEM graduate school, both in the initial (Column 1) and final rounds (Column 2) of the admission process, and are overall less likely to accept any admission offer (Column 3). On average, having to pay application fees decreases the likelihood of receiving any admission offer in the final round of the admission process by 11.1 percentage points, which represents a 14 percent reduction in this probability. Additionally, it reduces the probability of accepting any offer by 11.8 percentage points, representing an almost 20 percent reduction in this likelihood.

Figure 8: Impact of Application Fees on Admission Probability to a STEM Graduate School




(a) 1st Round

(b) Last Round

(c) Accept Admission Offer

*Notes:* The circles on the graph represent various probabilities related to the admission process for STEM graduate schools, as a function of the distance between parental income and the application fee waiver threshold (over the interval [-0.05, 0.05], which corresponds to the optimal bandwidth based on Calonico et al. (2015)). Panel a shows the probability of being admitted in the first round of the admission process, Panel b shows the probability of being admitted in the last round, and Panel c shows the probability of accepting an admission offer. The solid lines on the graph represent the estimated values obtained from a first-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver.

Table 5: Admission Probability to a STEM Graduate School

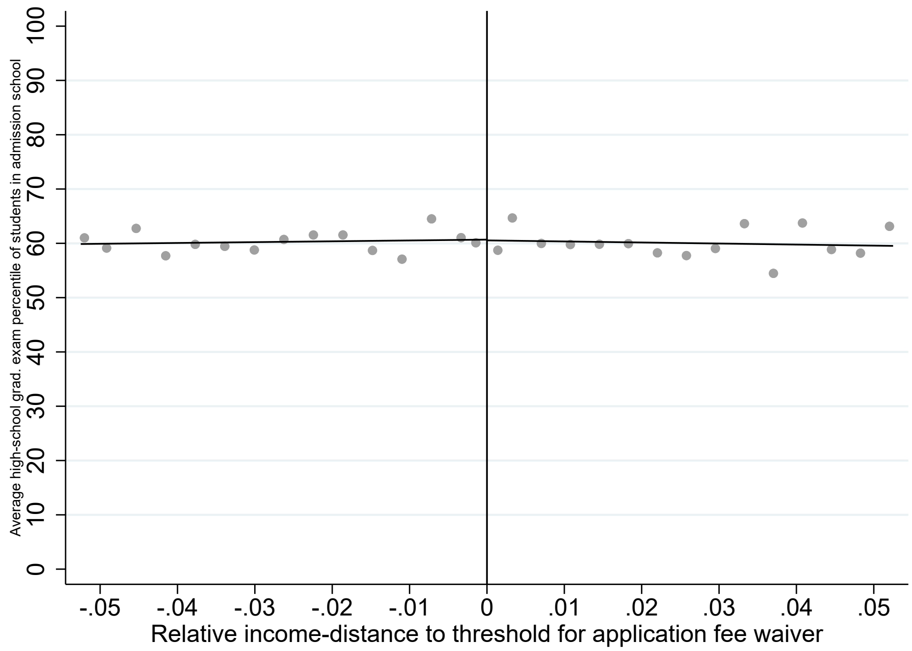
| | (1) Receive Admission Offer (1st round) | (2) Receive Admission Offer (Last round) | (3) Accept Admission Offer |
|---|---|---|---|
| Baseline mean (fee-waiver students) | 0.78 | 0.79 | 0.62 |
| Baseline RD estimate | -0.111** | -0.111** | -0.118** |
| | (0.054) | (0.051) | (0.057) |
| Robust 95% CI | [-0.216 ; -0.006] | [-0.211 ; -0.011] | [-0.230 ; -0.007] |
| Obs. used in estimation | 3,623 | 3,760 | 4,204 |
| Total number of obs. | 11,945 | 11,945 | 11,945 |

*Notes:* The table shows the estimated discontinuities in probability of admission around the application fee waiver threshold. Column 1 shows the probability of being admitted in the first round of the admission process, Column 2 shows the probability of being admitted in the last round, Column 3 shows the probability of accepting an admission offer. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

However, as indicated by Figure 9, upon receiving an admission offer from a STEM graduate school, there is no discernible difference in the selectivity of the institution for students who pay the application fees compared to those who are exempt. This suggests that students are indeed capable of effectively targeting the entrance exams they attempt based on their performance in preparatory programs.

**Removing the Waiver: Counterfactual Simulations.** The results highlight that low-income students benefiting from the fee waiver apply to significantly more STEM graduate schools and are more likely to receive admission offer from these schools. This raises the question of how their representation in STEM graduate schools would change if the fee waiver were to be removed. Leveraging the detailed nature of the data, which includes both students' preferences for programs and programs' preferences for students, I conduct counterfactual simulations of the graduate school-student matching algorithm under the assumption of fee waiver removal.

Figure 9: Selectivity of the Graduate School of Admission




*Notes:* The circles on the graph depict the average selectivity (in percentile) of the graduate school of admission for applicants who were admitted to at least one school, as a function of the distance between their parental income and the application fee waiver threshold (over the interval [-0.05, 0.05], which corresponds to the optimal bandwidth based on Calonico et al. (2015)). School selectivity is defined based on the average percentile rank at the high school graduation exam (*Baccalauréat*) of students admitted to the graduate schools. The solid lines on the graph represent the estimated values obtained from a first-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver.

*Reduction in the Number of Applications.* I must first estimate the counterfactual application set of fee-waiver students in the absence of the fee-waiver. I hypothesize that all fee-waiver students behave similarly to those at the threshold. Although this may seem like a strong assumption, it is reasonable because (i) fee waiver applicants further from the cutoff are typically lower-income compared to those at the threshold, likely exhibiting higher fee sensitivity. This suggests that results from this simulation exercise regarding the reduction of low-income students in STEM graduate schools should be conservative. Additionally, (ii) the number of entrance exams taken appears to be relatively flat on both sides of the exemption threshold (see Figure 7). Lastly, (iii) this assumption is less restrictive than suggesting that all fee-paying candidates would emulate the behavior of those near the threshold, particularly because there are significantly more candidates to the right of the threshold (74 percent of applicants are fee-paying candidates, Table B2). Moreover, high-income applicants are unlikely to behave in the same manner as applicants near the exemption threshold. Evidence from Figure 2 and Figure G7 shows that among fee-paying candidates, individuals from higher socio-economic backgrounds apply to a significantly larger number of graduate schools compared to students from lower socio-economic statuses. Meanwhile, no substantial differences are observed in the application decisions of fee-waiver candidates across different socio-economic backgrounds.

For each cluster of entrance exams, I initially estimate the decrease in the number of exams taken at the fee waiver eligibility threshold using Equation 4. I compute the percentage reduction in the number of entrance exams for each cluster $c$, denoted as $reduc_c$. Table G7 displays this percentage reduction for each of the 23 clusters of entrance exams. This approach is adopted at the cluster level rather than for individual exams to avoid relying on excessively variable estimates.[28] Subsequently, I proportionally reduce the number of entrance exams for fee waiver candidates. Specifically, I generate 300 vectors following a uniform distribution [0,1] ($u_i$) and remove exams for which ($u_i < |reduc_c|$), where $reduc_c$ represents the percentage reduction in the number of competitive exams taken for cluster $c$. Consequently, the proportion of entrance exams removed from each cluster of exams remains constant across all simulations, though the specific entrance exams eliminated vary randomly from one specification to another.

*School-Student Matching Algorithm.* Subsequently, I match this counterfactual application set of fee-waiver applicants — assumed under the scenario of removing the fee waiver — to determine which STEM graduate schools from their rank-ordered lists (ROLs) should be excluded, given that the applicants did not take entrance exams for those schools. ROLs of fee-paying applicants are left unchanged. I then rerun the school-student matching algorithm 300 times, maintaining constant the number of spots available in each STEM graduate program and the programs' preferences, but using the newly adjusted student preferences. For these simulations, I use entrance exams and admissions occurring in 2019 only.[29]

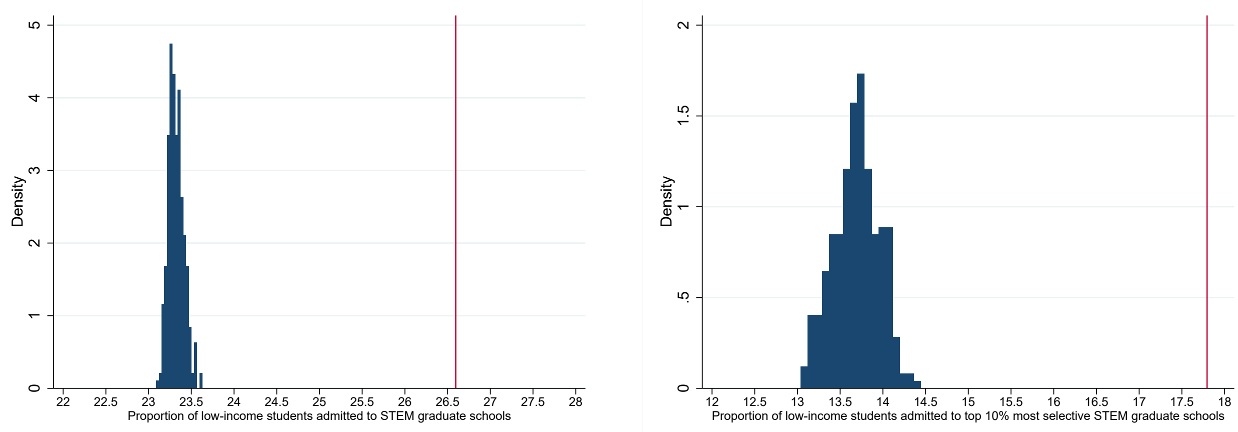
*Results.* Figures 10 display the results of these counterfactual simulations for the proportion of low-income students admitted to any STEM graduate school (Panel a) and to the top 10%

[28] Overall, there are 487 entrance exams divided into 23 clusters, corresponding to 4 to 5 clusters for each track. In the few instances (3 out of 23) where the estimated discontinuity is positive, suggesting that fee-paying candidates might take more exams, I postulate that there is no reduction at the fee waiver threshold for these exams, because (i) the discontinuity is not statistically significant in those three cases, and (ii) adding exams would necessitate stronger assumptions, as exam results for exams not taken by applicants remain unobservable. In cases where the estimated reduction in the number of exams exceeds 90 percent (4 out of 23), I assume a 90 percent reduction, so as not to systematically remove all entrance exams of these clusters.

[29] The estimation of the percentage reduction in the number of exams is based on all years in the RDD sample, while I focus on the year 2019 to run counterfactual simulations of the matching algorithm.

most selective STEM graduate schools (Panel b) in 2019.[30] The results indicate that, in the absence of the fee waiver, the proportion of low-income students (i.e., need-based grant students) in STEM graduate schools would be significantly reduced. Taking the median of all simulations, the results suggest that the proportion of need-based grant students admitted to STEM graduate schools would decrease by 3.3 percentage points (p.p.), corresponding to a 13% reduction. Their representation in the top 10% most selective graduate schools would further decrease by 4.1 p.p., representing a 23% decrease. Overall, the results suggest that the fee waiver increases the representation of low-income students among admittees to STEM graduate schools and the top 10% most selective ones.

Figure 10: Counterfactual Simulations: Effect of Removing Application Fee Waivers on the Proportion of Low-income Students Admitted to STEM Graduate Schools




(a) All STEM Graduate Schools

(b) Top 10% Most Selective STEM Grad. Schools

*Notes:* These figures depict results from 300 counterfactual simulations of the graduate school-student matching algorithm, assuming the removal of the fee waiver. The red bars represent the current proportion of need-based grants (low-income) receiving admission offers from STEM graduate schools (Panel a) and the top 10% most selective (Panel b), using data from the 2019 entrance exams. The blue bars depict this proportion under the counterfactual simulation scenario, also using data from the 2019 entrance exams. Selectivity of graduate schools is defined based on the average percentile rank at the national high school graduation exam of individuals admitted to the school. I define a reduced application set for low-income students, assuming all need-based grant recipients would behave similarly to those at the fee-waiver eligibility threshold. For each of the 23 clusters of entrance exams (4-5 clusters per track in the prep program), I calculate the percentage reduction in exams taken. Based on this estimation, I randomly remove some exams from the application set of low-income students. The proportion of exams removed by entrance exam cluster is consistent across all simulations, although the specific exams removed vary. New rank-ordered lists (ROLs) of schools for low-income students are then defined by removing schools requiring unattempted entrance exams, while ROLs for high-income students remain unchanged. Finally, I rerun the matching algorithm 300 times, adjusting for these new student preferences. The algorithm is based on a college-proposing version of the Gale-Shapley Deferred Acceptance mechanism.

[30] The selectivity of graduate schools is defined based on the average percentile rank at the national high school graduation exam of students admitted to the school.

### 6.3 On Enrollment Outcomes

**Enrollment probability.** Table 6 presents the main results in terms of enrollment outcomes, up to four academic years after the high-stakes entrance exams.[31] On average, the vast majority (between 95 to 97 percent) of fee waiver students are enrolled in higher education during the three academic years following the exams.[32] However, no difference is observed at the application fee waiver threshold in the likelihood of being enrolled in higher education for any of the four academic years following the high-stakes entrance exams to STEM graduate schools.

Despite the absence of an overall effect on enrollment rates, significant variation exists in the type of programs where fee waiver and fee-paying students are enrolled (Panel A of Table 6). Reflecting the decrease in admission probabilities to STEM graduate schools observed previously, there is a notable reduction in enrollment in these programs: a decrease of 15.4 percentage points (a 25 percent reduction) after one year, and 9.4 percentage points (a 12 percent reduction) after two or three years. In particular, fee-paying candidates demonstrate a reduced likelihood of enrolling in private STEM graduate programs (-6 p.p;, 60 percent reduction). These programs charge high tuition fees for all students. Therefore, the diminished propensity of fee-paying candidates to enroll in private programs can only be attributed to application fees rather than tuition fees. Conversely, fee-paying students are more likely to enroll in university programs, particularly in the academic year directly following entrance exams, with an increase of 10 percentage points (a 91 percent increase). However, this trend diminishes in subsequent years, indicating that some students are able to transition to STEM graduate programs for their master after initially enrolling in university programs to complete their bachelor's degree. There is no significant increase in the likelihood of students repeating preparatory programs (despite a positive yet non-significant coefficient, +2.3 percentage points, equivalent to a 10% increase). Fee-paying candidates might have a higher likelihood of enrolling in academic graduate schools (*Écoles Normales Supérieures*, ENS) in the second and

[31] Most STEM graduate school programs last for three years, but some students take longer to graduate, either because they enroll in a 4-year graduate program, repeat in a preparatory program, switch majors, or take a gap year. In fact, 58% of fee waiver students are still enrolled in higher education four years after taking the high-stakes entrance exams.

[32] The 3 to 5 percent of students not found in the administrative enrollment data (SISE-SIES) may be due to an incorrect student identifier in one of the two administrative data sources, because they are enrolled abroad, or in a program not covered by the administrative data, which are very few.

## Table 6: Effect of Application Fees on Enrollment Outcomes

| | Outcome in Year t+1 | | Outcome in Year t+2 | | Outcome in Year t+3 | | Outcome in Year t+4 | |
|---|---|---|---|---|---|---|---|---|
| | Baseline mean (1) | RD Est. (2) | Baseline mean (3) | RD Est. (4) | Baseline mean (5) | RD Est. (6) | Baseline mean (7) | RD Est. (8) |
| *Panel A. Enrollment* | | | | | | | | |
| Enrolled in higher education | 0.97 | -0.018<br>(0.018)<br>4,275<br>[11,945] | 0.96 | -0.004<br>(0.020)<br>3,868<br>[10,362] | 0.95 | 0.008<br>(0.028)<br>2,809<br>[ 8,430] | 0.58 | 0.008<br>(0.074)<br>2,100<br>[ 6,672] |
| Repeat in prep program | 0.21 | 0.023<br>(0.048)<br>3,887<br>[11,945] | | – | | – | | – |
| In STEM graduate school | 0.62 | -0.154***<br>(0.058)<br>3,997<br>[11,945] | 0.81 | -0.094**<br>(0.039)<br>4,703<br>[10,362] | 0.80 | -0.092*<br>(0.051)<br>3,037<br>[ 8,430] | 0.44 | -0.023<br>(0.066)<br>2,745<br>[ 6,672] |
| Among which in private program | 0.10 | -0.060**<br>(0.030)<br>4,955<br>[11,945] | 0.12 | -0.025<br>(0.032)<br>4,002<br>[10,362] | 0.11 | -0.038<br>(0.037)<br>2,719<br>[ 8,430] | 0.04 | 0.038<br>(0.027)<br>2,250<br>[ 6,672] |
| In university program | 0.12 | 0.100**<br>(0.041)<br>3,705<br>[11,945] | 0.12 | 0.057*<br>(0.034)<br>4,184<br>[10,362] | 0.11 | 0.058<br>(0.038)<br>3,303<br>[ 8,430] | 0.11 | 0.008<br>(0.048)<br>2,090<br>[ 6,672] |
| In academic graduate school (ENS) | 0.02 | 0.006<br>(0.013)<br>4,653<br>[11,945] | 0.03 | 0.031*<br>(0.018)<br>3,215<br>[10,362] | 0.03 | 0.038*<br>(0.022)<br>2,540<br>[ 8,430] | 0.03 | 0.018<br>(0.026)<br>2,043<br>[ 6,672] |
| *Panel B. Selectivity of program* | | | | | | | | |
| Average selectivity of the program | 0.69 | -0.016<br>(0.018)<br>3,814<br>[11,945] | 0.70 | 0.007<br>(0.016)<br>3,706<br>[10,362] | 0.70 | 0.011<br>(0.017)<br>3,501<br>[ 8,430] | 0.72 | -0.015<br>(0.033)<br>967<br>[ 6,672] |
| for those enrolled STEM graduate schools | 0.75 | 0.038*<br>(0.020)<br>1,655<br>[ 5,298] | 0.75 | 0.034*<br>(0.017)<br>1,701<br>[ 6,179] | 0.75 | 0.033*<br>(0.018)<br>1,770<br>[ 4,998] | 0.78 | 0.011<br>(0.018)<br>1,620<br>[ 2,339] |
| for those enrolled at the university | 0.57 | -0.041<br>(0.031)<br>813<br>[ 3,432] | 0.59 | -0.001<br>(0.026)<br>1,014<br>[ 3,500] | 0.59 | 0.004<br>(0.029)<br>849<br>[ 2,728] | 0.58 | -0.002<br>(0.051)<br>316<br>[ 1,290] |

*Notes:* This table presents the estimated discontinuities in enrollment outcomes for applicants who took high-stakes entrance exams between 2015 and 2021, from one year after they took the exams (Column 2) to four years later (Column 8). Selectivity of programs is defined by the average percentile ranks of individuals enrolled in the same program, whether at the same university or within the same STEM graduate school. Each coefficient represents the outcome of a separate nonparametric fuzzy regression discontinuity analysis, based on Calonico et al. (2017). The applicant's relative income distance to the application fee waiver threshold serves as the running variable. The first column for each outcome displays the mean value of the dependent variable for fee waiver applicants. Robust standard errors are presented in parentheses next to each coefficient and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The number of observations used in the regression discontinuity (RD) estimation is indicated below each estimate, while the total number of observations in the sample is shown in brackets. Enrollment outcomes are observed up to the 2021-2022 academic year. Outcome data for the first year include the full sample (applicants taking high-stakes entrance exams from 2015 to 2021). For analyses of outcomes in subsequent years, the sample is restricted to earlier applicants to ensure the availability of outcome data: applicants from 2015 to 2020 for outcomes in year t+2, from 2015 to 2019 for outcomes in year t+3, and from 2015 to 2018 for outcomes in year t+4.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

third years after taking the exams, where there is an observed increase of 3.1 to 3.8 percentage points (more than 100 percent increase), significant at the 10 percent level only. These graduate schools are characterized by the absence of application and tuition fees and provide salaries to approximately half of their students. Therefore, they may be particularly attractive to students who do not benefit from need-based grants but are on the margin of doing so.

**Selectivity of the program.** Panel B of Table 6 presents the outcomes in terms of the selectivity of the program of enrollment. Selectivity is defined by the level of peers in the program, as the average percentile rank at the high school graduation exam of individuals enrolled in the same program (i.e., same university or same STEM graduate school). The analysis reveals no significant change in the selectivity of the programs to which individuals are enrolled across any of the four years following their participation in the high-stakes entrance exams for elite graduate schools. As fee-paying candidates enroll more often in university programs, this finding is particularly unexpected given the general perception that STEM graduate programs are more selective, on average, than university programs. Further analysis, disaggregating selectivity by program type, indicates a nuanced dynamic: fee-paying candidates who do enroll in STEM graduate programs tend to enroll in more selective institutions. Thus, two opposing trends emerge: a decreased likelihood of fee-paying candidates enrolling in STEM graduate programs, counterbalanced by their enrollment in more selective ones when they do. Moreover, they enroll in relatively selective university programs, where the average percentile rank of enrollees is between 0.57 and 0.59. In comparison, the average percentile rank for all university programs is 0.52, and a rank of 0.59 places a program in the top 25% of all programs in terms of selectivity. These dynamics explain the observed lack of overall difference in program selectivity.

**Expected earnings of programs.** Fee-paying candidates attend programs that are, on average, equally selective as those attended by fee-waiver candidates. Given the common view that STEM graduate schools provide solid labor market prospects, to what extent can fee-paying candidates attend programs that offer comparably favorable outcomes in terms of earnings? In the absence of individual labor market data on the transition into the labor market and indi-

Table 7: Effect of Application Fees on Expected Earnings, One Year After Graduation

| | Outcome in Year t+1 | | Outcome in Year t+2 | | Outcome in Year t+3 | | Outcome in Year t+4 | |
|---|---|---|---|---|---|---|---|---|
| | Baseline mean (1) | RD Est. (2) | Baseline mean (3) | RD Est. (4) | Baseline mean (5) | RD Est. (6) | Baseline mean (7) | RD Est. (8) |
| *Panel A. All students* | | | | | | | | |
| Expected earnings (in €) | 37,510 | -1,708* | 37,167 | 184 | 36,857 | -443 | 36,536 | -917 |
| | | ( 952) | | ( 664) | | ( 687) | | ( 766) |
| | | 2,034 | | 3,101 | | 2,321 | | 1,715 |
| | | [6,552] | | [7,334] | | [6,117] | | [4,920] |
| *Panel B. Male students* | | | | | | | | |
| Expected earnings (in €) | 38,047 | -1,276 | 37,721 | 303 | 37,420 | -30 | 37,073 | 472 |
| | | (1,472) | | (1,000) | | ( 909) | | ( 894) |
| | | 1,237 | | 1,657 | | 1,647 | | 1,497 |
| | | [4,446] | | [5,061] | | [4,217] | | [3,396] |
| *Panel C. Female students* | | | | | | | | |
| Expected earnings (in €) | 36,349 | -1,528 | 35,886 | -373 | 35,550 | -310 | 35,271 | -1,442* |
| | | (1,040) | | ( 703) | | ( 723) | | ( 861) |
| | | 940 | | 1,547 | | 1,360 | | 1,083 |
| | | [2,106] | | [2,273] | | [1,900] | | [1,524] |

*Notes:* This table presents the estimated discontinuities in expected earnings one year after graduation, from the program students are enrolled in one year after they took the entrance exams (Column 2) to four years later (Column 8). Panel A displays results for all students, Panel B for male students and Panel C for female students. Data on expected earnings one year after graduation represent gross earnings, including bonuses, disaggregated by gender for STEM graduate school earnings data. Data are sourced from CTI (*Commission des Titres d'Ingénieurs*) for expected earnings of STEM graduate schools students and from MESRI-OPEN DATA for expected earnings of university students. Data are available at the program × cohort level, and imputations are used for missing values. Each coefficient represents the outcome of a separate nonparametric fuzzy regression discontinuity analysis, based on Calonico et al. (2017). The applicant's relative income distance to the application fee waiver threshold serves as the running variable. The first column for each outcome displays the mean value of the dependent variable for fee waiver applicants.Robust standard errors are presented in parentheses next to each coefficient and are clustered at the *track × program × cohort* level. The number of observations used in the regression discontinuity (RD) estimation is indicated below each estimate, while the total number of observations in the sample is shown in brackets. Enrollment outcomes are observed up to the 2021-2022 academic year. Outcome data for the first year include the full sample (applicants taking high-stakes entrance exams from 2015 to 2021). Analyses for subsequent years restrict the sample to earlier applicants to ensure the availability of outcome data (applicants from 2015 to 2020 for outcomes in year t+2, from 2015 to 2019 for outcomes in year t+3, and from 2015 to 2018 for outcomes in year t+4).
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

viduals' earnings, I rely on publicly available data on the earnings of graduates at the program $\times$ cohort level, further disaggregated by gender for STEM graduate school programs.[33] Table 7 shows the estimated discontinuities in expected earnings at the fee waiver threshold for programs in which students enroll from one year (column 2) to four years (column 8) after taking the high-stakes entrance exams. Overall, no significant differences are observed in terms of expected earnings. If anything, fee-paying candidates might initially enroll in programs with slightly worse labor market prospects (€-1,700, approximately a 5 percent reduction, significant at the 10 percent level) just the year after graduation. However, they are able to enroll in programs with as good labor market prospects as fee waiver candidates in years t+2 and t+3, which typically correspond to the master's degree for most students. For women who remain enrolled in higher education four years after taking the entrance exams, there is some suggestive evidence that the last program in which they are enrolled offers slightly lower expected earnings for fee-paying candidates compared to fee waiver candidates (-€1,400, around a 4 percent reduction, significant at the 10 percent level). Results might vary with data on earnings later in the career or with individual labor market data.

In this section, the analysis reveals no significant change in either the probability of enrollment or the selectivity of programs at the fee waiver threshold. Subsequent analysis will delve into these results by gender, unveiling more nuanced dynamics.

### 6.4 Robustness Tests

I present robustness tests of the main results regarding admission to STEM graduate school in Section E.5 of the Appendix.

**Varying bandwidth and polynomial order.** In Table J10, I examine the robustness of my main results to varying bandwidth size and polynomial order. The point estimates range from a 9.2 to a 20.2 percentage point decrease in admission probability, but remain statistically significant at

[33]The data are sourced from CTI (*Commission des Titres d'Ingénieurs*) for expected earnings of STEM graduate school students and from MESRI-OPEN DATA for expected earnings of university students. The data from university programs only include STEM majors, as the vast majority of students from STEM prep programs enroll in those majors when not gaining admission to a STEM graduate school. Expected earnings refer to the gross median salary of alumni one year (for STEM graduate schools) to 18 months (for university programs) after graduation. More information is provided in the Data section of the article.

either the 1 percent or 5 percent level across all specifications. This reinforces the conclusion that application fees negatively impact students' chances of being admitted to any STEM graduate school. The most conservative estimate, using twice the optimal bandwidth, indicates a 9.2 percentage point decrease in admission probability for individuals required to pay application fees, representing a 12 percent reduction in this probability, which is still substantial.

**Controlling for track fixed-effects.** In Table K11, I run a robustness check of the main results controlling for track fixed-effects, due to some imbalances in the tracks around the fee waiver eligibility threshold (Table 2). Results are very similar to the main estimates.

**Focusing on all prep program students.** In Table L12, I check that among the full sample of first-year prep program students, the probability of taking entrance exams is not discontinuous at the threshold. This is confirmed as the coefficient is exactly 0. I also run a robustness check of the main results in the full sample of first-year prep program students. Results are similar to the main estimates, although less precisely estimated (Table M13).

**Focusing on exams with no application fees.** In Table N14, I present results regarding the probability of applying to schools with free exams (both all graduate schools and top schools (*Écoles Normales Supérieures*)). As expected, the applications to these schools do not vary. Fee-paying candidates are more likely to gain admission to a free school, which can be explained by their emphasis on these schools compared to fee-paying ones. These schools do not levy tuition fees either, making them particularly attractive to students not eligible for fee waivers but on the verge of eligibility.

**Controlling for the number of entrance exams taken.** To confirm that application fees cause lower admission probability, I analyze the outcomes in Table 5 while controlling for the number of exams taken. If lower admission probability is due to taking fewer exams, there should be no difference in admission rates between those who pay fees and those who do not when the number of exams taken is controlled for. Table O15 shows that, when controlling for the number of exams taken, there is no significant difference in admission probability between fee-waiver and fee-paying students. The point estimates are still negative, especially for the probability of accepting an admission offer, indicating that fee-paying students might be less satisfied with their admission proposals.

## 6.5 Heterogeneity Results

Table 8: Heterogeneity in the Number of Exams Taken

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Men | Women | High Ses | Medium & Low Ses | High Ability | Low Ability |
| Baseline mean (fee-waiver students) | 23.40 | 21.42 | 22.98 | 22.63 | 21.51 | 24.17 |
| Baseline RD estimate | -15.53*** | -8.90*** | -10.69*** | -13.60*** | -10.81*** | -14.50*** |
| | (1.73) | (2.32) | (1.87) | (1.83) | (1.90) | (1.85) |
| Difference p-value: | .02 | | .27 | | .16 | |
| Robust 95% CI | [-18.9 ; -12.1] | [-13.4 ; -4.4] | [-14.3 ; -7.0] | [-17.2 ; -10.0] | [-14.5 ; -7.1] | [-18.1 ; -10.9] |
| Obs. used in estimation | 2,356 | 1,395 | 2,303 | 1,915 | 1,761 | 2,076 |
| Total number of obs. | 8,158 | 3,787 | 5,251 | 6,694 | 5,943 | 5,894 |

*Notes:* The table displays estimated discontinuities in the number of exam taken around the application fee waiver threshold, broken down by gender (male and female), socioeconomic status (high and medium & low), and ability level (high and low). Socioeconomic status is determined based on the Department of Education's statistical service (DEPP). High socioeconomic status (SES) includes professionals, managers, CEOs, teachers, and artists. Medium and Low SES include all other occupations. The SES of the child's legal representative is used for classification. High ability students are those who obtained their high school graduation exam with highest honors, and low ability students are those who did not obtain the high school graduation exam with highest honors. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Robust standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 2 underscores that among fee-paying applicants, those from lower socio-economic background take less exams than those from a higher socio-economic status. This suggests the possibility of varying effects across different socio-economic status, a hypothesis corroborated by the estimation results presented in Tables 8 and 9. Interestingly, there is a correlation between the reduction in the number of entrance exams taken (as shown in Table 8) and the decreased probability of admission (Table 9). This suggests that the lowered admission likelihood is indeed a consequence of fewer exams being taken. Specifically, male students, those from lower socio-economic backgrounds (SES), and students with initially lower abilities tend to reduce more the number of exams they take when having to pay fees, which in turn diminishes their probability of admission to any STEM graduate school. At the fee exemption threshold, the admission likelihood for females, individuals from higher SES backgrounds, and those with initially higher abilities is not significantly adversely affected. However, for students from low SES backgrounds, the results are particularly notable: there is an 18.1 percentage point decrease in the admission probability for individuals required to pay fees compared to those exempted, amounting to a 24 percent reduction in the probability of admission to any STEM graduate school.

Table 9: Heterogeneity in Admission Probability to a STEM Graduate School

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Men | Women | High Ses | Medium & Low Ses | High Ability | Low Ability |
| Baseline mean (fee-waiver students) | 0.80 | 0.77 | 0.83 | 0.76 | 0.87 | 0.72 |
| Baseline RD estimate | -0.176*** | -0.007 | 0.003 | -0.181*** | -0.046 | -0.128* |
| | (0.065) | (0.069) | (0.068) | (0.060) | (0.064) | (0.072) |
| Difference p-value: | .07 | | .04 | | .39 | |
| Robust 95% CI | [-0.3 ; -0.0] | [-0.1 ; 0.1] | [-0.1 ; 0.1] | [-0.3 ; -0.1] | [-0.2 ; 0.1] | [-0.3 ; 0.0] |
| Obs. used in estimation | 2,409 | 1,748 | 1,877 | 2,584 | 1,743 | 1,947 |
| Total number of obs. | 8,158 | 3,787 | 5,251 | 6,694 | 5,943 | 5,894 |

*Notes:* The table displays the estimated discontinuities in probability of admission in the final round of the admission process around the application fee waiver threshold, broken down by gender (male and female), socioeconomic status (high and medium & low), and ability level (high and low). Socioeconomic status is determined based on the Department of Education's statistical service (DEPP). High socioeconomic status (SES) includes professionals, managers, CEOs, teachers, and artists. Medium and Low SES include all other occupations. The SES of the child's legal representative is used for classification. High ability students are those who obtained their high school graduation exam with highest honors, and low ability students are those who did not obtain the high school graduation exam with highest honors. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Heterogeneity results by socio-economic status (SES) and previous ability are somewhat expected, as these individuals are potentially more credit constrained, and reduce their set of applications more when having to pay application fees (Table 8). The mechanism explaining why men are more impacted at the fee waiver threshold than women is less clear. In Table 10, I further investigate this mechanism by examining the selectivity of exams attempted, broken down by gender. Exam selectivity is defined as the average percentile rank at the high school graduation exam of students attempting the exam. My findings indicate that male students, when required to pay fees, tend to reduce the range of selectivity of schools they apply to more significantly than female students (they reduce this range by -3.3 percentile rank, as opposed to a non-significant -1.13 for female students).[34] Interestingly, when having to pay fees, male students typically increase the minimum selectivity of schools applied to, thereby limiting their *safety choices*. In contrast, female students tend to reduce their applications to the most selective schools, thus limiting their *ambitious choices*. These application patterns align with the conceptual framework discussed in Section 3, with female students being more risk-averse than male students. This observation complements existing literature on gender and risk aversion (summarized in Dohmen et al. (2011); Filippin (2022)). Closely related to my results, Saygin (2016) showed that in Turkey, female students apply to less selective programs and end up in less selective institutions than male students for a given test score; this is explained by their greater aversion to being unassigned. In my setting, female students may also exhibit greater aversion to being unassigned, which could lead them to reduce their number of exam applications less drastically when facing fees, and to more commonly limit their applications to ambitious choices rather than safe ones. These application patterns could explain the observed gender heterogeneity in admission outcomes: having to pay the fees reduces the likelihood of admission by 23 percent for male students but does not significantly affect the admission chances of female students.

**Enrollment outcomes by gender.** Tables 11 and 12 present the enrollment outcomes by gender. While the previous section revealed no aggregated difference at the threshold in enrollment probabilities and program selectivity, these outcomes conceal some gender heterogeneity. As might be anticipated, given that only the admission probabilities of men are negatively affected, the likelihood of their enrollment in higher education when they pay the application fees, one year after taking the entrance exams, is 4.6 percentage points lower (approximately a 5 percent reduction, significant at the 10 percent level) than that of fee waiver candidates, suggesting that some fee-paying men take a gap year just the year following the exams. No significant difference in enrollment probability is observed in years 2, 3, and 4 after taking the

[34] This range is calculated as the difference between the most and least selective entrance exams taken.

## Table 10: Gender Heterogeneity in Selectivity of Exams Attempted

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Range of Selectivity (Men) | Range of Selectivity (Women) | Minimum Selectivity (Men) | Minimum Selectivity (Women) | Maximum Selectivity (Men) | Maximum Selectivity (Women) |
| Baseline mean (fee-waiver students) | 12.60 | 11.01 | 71.18 | 73.04 | 83.78 | 84.05 |
| Baseline RD estimate | -3.32*** | -1.13 | 2.33** | -0.37 | -0.74 | -1.49** |
| | (0.81) | (1.07) | (1.12) | (1.27) | (0.77) | (0.72) |
| Difference p-value: | .1 | | .11 | | .48 | |
| Robust 95% CI | [-4.91 ; -1.73] | [-3.23 ; 0.98] | [ 0.14 ; 4.52] | [-2.85 ; 2.11] | [-2.25 ; 0.78] | [-2.90 ; -0.08] |
| Obs. used in estimation | 2,381 | 1,754 | 2,459 | 1,751 | 3,280 | 1,757 |
| Total number of obs. | 8,158 | 3,787 | 8,158 | 3,787 | 8,158 | 3,787 |

*Notes:* The table displays the estimated discontinuities in selectivity of exams attempted (range of selectivity, minimum selectivity and maximum selectivity), around the application fee waiver threshold, broken down by gender (male and female). Selectivity of exams is defined with the average percentile rank at high school graduation exams of students attempting these exams. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

high-stakes entrance exams, but the coefficient for year 4 is positive and relatively large (+6.4 p.p. or 11 percent increase), which could suggest that fee-paying men might take longer to graduate than fee-waiver men. Specifically, men are notably less likely to be enrolled in STEM graduate programs one year after the exams (a 25.9 percentage point reduction, or 45 percent reduction). They are not significantly more likely to be enrolled in university programs, even if the coefficient for year 1 is relatively high. In years 2 and 3 after taking the exams, they are more likely to be enrolled in an academic STEM graduate school, ENS (+6.4 percentage points or 213 percent increase), which could be explained by the possibility that they are more likely to repeat in preparatory programs when paying the fees and repeating helps getting into the more selective graduate schools. Although the coefficient is not significant, it is relatively large (+9.6 percentage points or 44 percent increase).

This stands in stark contrast to the results for women (Table 12), for whom the probability of repeating when paying the application fees is negative, though not significant (-9.6 percentage points or a 46 percent reduction). Unlike the men, the probabilities of women being enrolled in higher education are not affected by having to pay application fees, and specifically, the probability of being enrolled in STEM graduate schools is not impacted (even though the coefficient for year 2 is negative, it is not significant). However, in contrast to male students for whom the selectivity of programs is not affected on average (fee-paying men being less enrolled in STEM graduate schools, but enrolled in more selective ones), the program selectivity of women is affected by having to pay application fees, but only in the first year after taking the exams (-5.9 percentage points or a 9 percent reduction in selectivity). These effects are limited to enrollment in the academic year immediately after the high-stakes entrance exams and do not persist, suggesting that students are cognizant of program quality and capable of securing admission to reputable master's programs.

These findings align with the observation that men tend to forgo their *safe choices*, while women are more likely to abandon their *ambitious choices*, as shown in Table 10.

Table 11: Effect of Application Fees on Enrollment Outcomes: Male Students

| | Outcome in Year t+1 | | Outcome in Year t+2 | | Outcome in Year t+3 | | Outcome in Year t+4 | |
|---|---|---|---|---|---|---|---|---|
| | Baseline mean (1) | RD Est. (2) | Baseline mean (3) | RD Est. (4) | Baseline mean (5) | RD Est. (6) | Baseline mean (7) | RD Est. (8) |
| *Panel A. Enrollment* | | | | | | | | |
| Enrolled in higher education | 0.97 | -0.046*<br>(0.027)<br>2,331<br>[ 8,158] | 0.97 | -0.013<br>(0.023)<br>2,662<br>[ 7,079] | 0.95 | -0.001<br>(0.032)<br>2,385<br>[ 5,759] | 0.59 | 0.065<br>(0.098)<br>1,355<br>[ 4,575] |
| Repeat in prep program | 0.21 | 0.096<br>(0.066)<br>2,152<br>[ 8,158] | | – | | – | | – |
| In STEM graduate school | 0.62 | -0.258***<br>(0.069)<br>2,842<br>[ 8,158] | 0.81 | -0.102**<br>(0.048)<br>3,190<br>[ 7,079] | 0.81 | -0.110*<br>(0.060)<br>2,389<br>[ 5,759] | 0.44 | -0.018<br>(0.096)<br>1,574<br>[ 4,575] |
| Among which in private program | 0.10 | -0.084**<br>(0.038)<br>3,269<br>[ 8,158] | 0.12 | -0.022<br>(0.043)<br>2,632<br>[ 7,079] | 0.12 | -0.008<br>(0.045)<br>2,248<br>[ 5,759] | 0.04 | 0.050<br>(0.042)<br>1,484<br>[ 4,575] |
| In university program | 0.11 | 0.085<br>(0.052)<br>2,365<br>[ 8,158] | 0.11 | 0.026<br>(0.041)<br>2,982<br>[ 7,079] | 0.10 | 0.058<br>(0.047)<br>2,086<br>[ 5,759] | 0.10 | 0.007<br>(0.053)<br>1,911<br>[ 4,575] |
| In academic graduate school (ENS) | 0.02 | 0.033*<br>(0.020)<br>2,487<br>[ 8,158] | 0.03 | 0.063**<br>(0.026)<br>1,933<br>[ 7,079] | 0.03 | 0.050<br>(0.031)<br>2,198<br>[ 5,759] | 0.04 | 0.038<br>(0.034)<br>1,892<br>[ 4,575] |
| *Panel B. Selectivity of program* | | | | | | | | |
| Average selectivity of the program | 0.69 | 0.004<br>(0.027)<br>1,746<br>[ 8,158] | 0.70 | 0.028<br>(0.023)<br>1,875<br>[ 7,079] | 0.70 | 0.016<br>(0.028)<br>1,426<br>[ 5,759] | 0.72 | 0.005<br>(0.044)<br>540<br>[ 4,575] |
| for those enrolled STEM graduate schools | 0.75 | 0.058**<br>(0.028)<br>1,023<br>[ 3,648] | 0.75 | 0.047*<br>(0.024)<br>1,020<br>[ 4,238] | 0.75 | 0.042<br>(0.027)<br>1,010<br>[ 3,419] | 0.77 | 0.010<br>(0.031)<br>646<br>[ 1,627] |
| for those enrolled at the university | 0.58 | -0.040<br>(0.042)<br>502<br>[ 2,249] | 0.59 | 0.007<br>(0.039)<br>588<br>[ 2,341] | 0.59 | -0.002<br>(0.045)<br>460<br>[ 1,830] | 0.59 | 0.052<br>(0.065)<br>260<br>[ 872] |

*Notes:* This table presents the estimated discontinuities in enrollment outcomes for male applicants who took high-stakes entrance exams between 2015 and 2021, from one year after they took the exams (Column 2) to four years later (Column 8). Selectivity of programs is defined by the average percentile ranks of individuals enrolled in the same program, whether at the same university or within the same STEM graduate school. Each coefficient represents the outcome of a separate nonparametric fuzzy regression discontinuity analysis, based on Calonico et al. (2017). The applicant's relative income distance to the application fee waiver threshold serves as the running variable. The first column for each outcome displays the mean value of the dependent variable for fee waiver applicants. Robust standard errors are presented in parentheses next to each coefficient and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The number of observations used in the regression discontinuity (RD) estimation is indicated below each estimate, while the total number of observations in the sample is shown in brackets. Enrollment outcomes are observed up to the 2021-2022 academic year. Outcome data for the first year include the full sample (applicants taking high-stakes entrance exams from 2015 to 2021). Analyses for subsequent years restrict the sample to earlier applicants to ensure the availability of outcome data (applicants from 2015 to 2020 for outcomes in year t+2, from 2015 to 2019 for outcomes in year t+3, and from 2015 to 2018 for outcomes in year t+4).
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

## Table 12: Effect of Application Fees on Enrollment Outcomes: Female Students

| | Outcome in Year t+1 | | Outcome in Year t+2 | | Outcome in Year t+3 | | Outcome in Year t+4 | |
|---|---|---|---|---|---|---|---|---|
| | Baseline mean | RD Est. | Baseline mean | RD Est. | Baseline mean | RD Est. | Baseline mean | RD Est. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Panel A. Enrollment* | | | | | | | | |
| Enrolled in higher education | 0.97 | 0.014 | 0.96 | -0.009 | 0.94 | 0.005 | 0.58 | 0.007 |
| | | (0.025) | | (0.025) | | (0.031) | | (0.083) |
| | | 1,568 | | 2,405 | | 1,975 | | 1,532 |
| | | [ 3,787] | | [ 3,283] | | [ 2,671] | | [ 2,097] |
| Repeat in prep program | 0.21 | -0.097 | | – | | – | | – |
| | | (0.067) | | | | | | |
| | | 1,623 | | | | | | |
| | | [ 3,787] | | | | | | |
| In STEM graduate school | 0.61 | 0.028 | 0.81 | -0.084 | 0.80 | -0.007 | 0.43 | 0.055 |
| | | (0.087) | | (0.052) | | (0.058) | | (0.082) |
| | | 1,553 | | 2,432 | | 1,973 | | 1,530 |
| | | [ 3,787] | | [ 3,283] | | [ 2,671] | | [ 2,097] |
| Among which in private program | 0.09 | -0.016 | 0.11 | -0.030 | 0.11 | -0.041 | 0.03 | 0.016 |
| | | (0.045) | | (0.037) | | (0.040) | | (0.029) |
| | | 1,712 | | 2,364 | | 1,977 | | 1,273 |
| | | [ 3,787] | | [ 3,283] | | [ 2,671] | | [ 2,097] |
| In university program | 0.14 | 0.126** | 0.13 | 0.073 | 0.12 | 0.002 | 0.11 | -0.065 |
| | | (0.062) | | (0.047) | | (0.050) | | (0.054) |
| | | 1,516 | | 2,249 | | 2,015 | | 1,564 |
| | | [ 3,787] | | [ 3,283] | | [ 2,671] | | [ 2,097] |
| In academic graduate school (ENS) | 0.01 | -0.041*** | 0.02 | -0.009 | 0.02 | -0.005 | 0.02 | -0.001 |
| | | (0.016) | | (0.014) | | (0.014) | | (0.019) |
| | | 1,554 | | 2,370 | | 1,787 | | 1,569 |
| | | [ 3,787] | | [ 3,283] | | [ 2,671] | | [ 2,097] |
| *Panel B. Selectivity of program* | | | | | | | | |
| Average selectivity of the program | 0.68 | -0.059** | 0.70 | -0.010 | 0.70 | -0.011 | 0.72 | 0.031 |
| | | (0.028) | | (0.018) | | (0.029) | | (0.031) |
| | | 1,248 | | 2,301 | | 735 | | 839 |
| | | [ 3,787] | | [ 3,283] | | [ 2,671] | | [ 2,097] |
| for those enrolled STEM graduate schools | 0.75 | 0.009 | 0.76 | 0.028* | 0.76 | 0.022 | 0.79 | – |
| | | (0.030) | | (0.017) | | (0.024) | | – |
| | | 455 | | 1,404 | | 534 | | – |
| | | [ 1,650] | | [ 1,941] | | [ 1,579] | | – |
| for those enrolled at the university | 0.57 | -0.028 | 0.58 | -0.009 | 0.58 | 0.010 | 0.58 | -0.029 |
| | | (0.039) | | (0.025) | | (0.038) | | (0.063) |
| | | 383 | | 844 | | 315 | | 131 |
| | | [ 1,183] | | [ 1,159] | | [ 898] | | [ 418] |

*Notes:* This table presents the estimated discontinuities in enrollment outcomes for female applicants who took high-stakes entrance exams between 2015 and 2021, from one year after they took the exams (Column 2) to four years later (Column 8). Selectivity of programs is defined by the average percentile ranks of individuals enrolled in the same program, whether at the same university or within the same STEM graduate school. Each coefficient represents the outcome of a separate nonparametric fuzzy regression discontinuity analysis, based on Calonico et al. (2017). The applicant's relative income distance to the application fee waiver threshold serves as the running variable. The first column for each outcome displays the mean value of the dependent variable for fee waiver applicants. Robust standard errors are presented in parentheses next to each coefficient and are clustered at the *track* × *program* × *cohort* level. The number of observations used in the regression discontinuity (RD) estimation is indicated below each estimate, while the total number of observations in the sample is shown in brackets. Enrollment outcomes are observed up to the 2021-2022 academic year. Outcome data for the first year include the full sample (applicants taking high-stakes entrance exams from 2015 to 2021). Analyses for subsequent years restrict the sample to earlier applicants to ensure the availability of outcome data (applicants from 2015 to 2020 for outcomes in year t+2, from 2015 to 2019 for outcomes in year t+3, and from 2015 to 2018 for outcomes in year t+4).

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

## 6.6 One by One or All Together? Application Fee Design

Which characteristics of the programs are determinant in students' choice of which competitive exams to apply to when facing application fees? As detailed in Table 3, fee paying candidates reduce more the number of competitive entrance exams they apply to (by 60%) compared to the total number of graduate schools (by 30%). This fact suggests that fee-paying candidates are more inclined to eliminate entrance exams associated with fewer schools rather than those providing access to a larger number of graduate schools.

In this section, the focus will be on the design of application fees, by studying two distinct groups of schools: one group, referred to as Cluster 1 (*Banque Centrale*), employs a decentralized fee schedule, meaning applicants must pay separate fees for each graduate schools, although the entrance exams are the same for all of those schools; the other group, referred to as Cluster 2 (*Banque Mines-Ponts*), employs a centralized fee schedule, requiring applicants to pay a single, larger fee that covers entrance exams for all graduate schools in the cluster.[35]

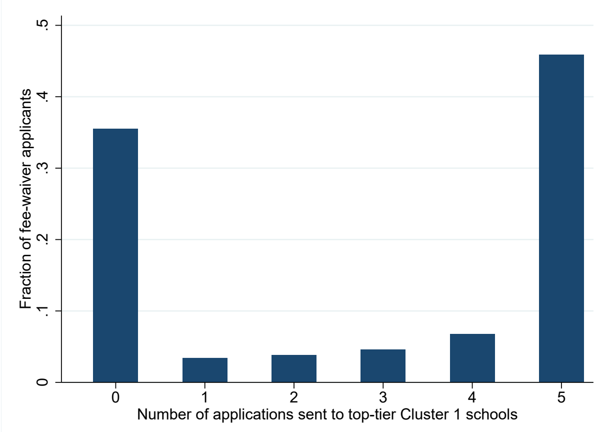
**Application Behavior.** I first observe the application behavior of students applying to graduate schools that follow a decentralized fee schedule. Figure 11 illustrates that, among the five primary schools in this cluster,[36] the majority of fee-waiver applicants (Panel a) either do not apply to any school in this cluster (35 percent) or apply to all five schools (45 percent). This trend can be attributed to the fact that these schools share a common entrance exam, and since these students are not required to pay any fees, there is no incentive to limit their applications. Consequently, they can apply to all five schools and later decide their preferences over those schools. Conversely, students who are required to pay application fees (Panel b) exhibit a more cautious approach in selecting the schools to which they apply. 45 percent of these students do not apply to any graduate school in the cluster. Among those who do apply, there is a varied distribution, with some students applying to just one school, while others apply to two, three, four, or all five graduate schools. This distribution can be attributed to the additional cost of 120 euros incurred with each additional application. Slightly less than 15 percent of the fee-paying students apply to all five schools, compared to over 45 percent of the fee-waiver students. This

[35] Interestingly, Cluster 1, which generally uses a decentralized fee schedule, has implemented a centralized fee schedule for one of its four tracks (track 4, PT) since 2016.

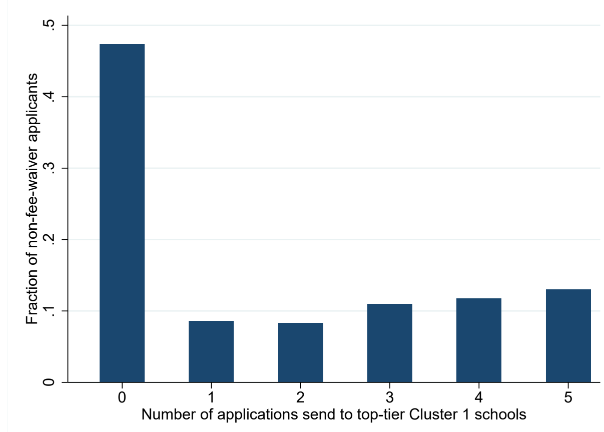
[36] *Centrale-Supélec*, *Centrale Lille*, *Centrale Lyon*, *Centrale Marseille*, and *Centrale Nantes*.

underscores the significant impact that application fees have on the decision-making process of prospective students. This also implies that there may be students who perform well enough in the exams to secure admission to one of the most selective schools within the cluster, but are unable to gain admission solely because they did not pay the application fee for that specific school.

Figure 11: Number of Applications Send to Top-Tier Graduate Schools With Decentralized Application Fees, by Application Fee Waiver Status




(a) Fee-Waiver Applicants

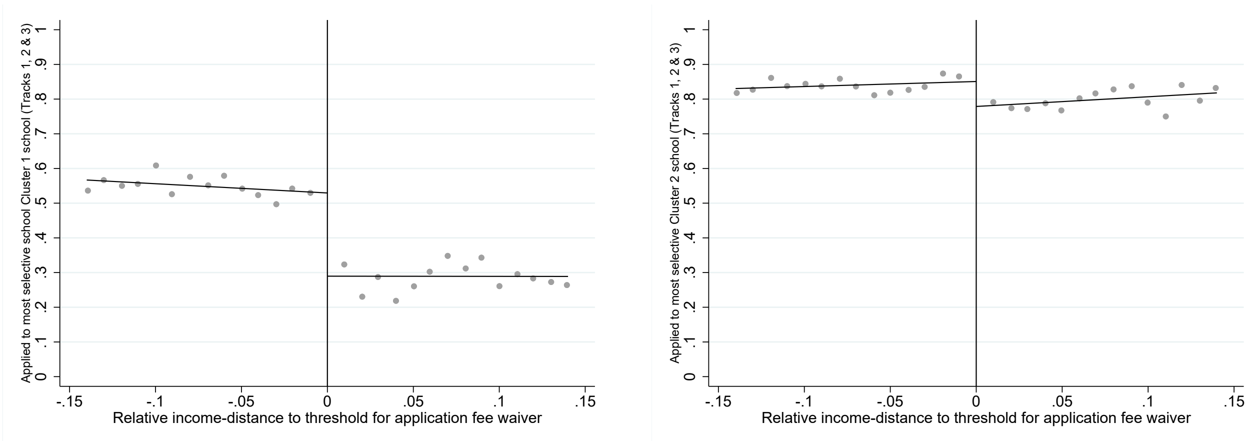



(b) Non-Fee-Waiver Applicants

*Notes:* The histograms depict the number of applications submitted to top-tier schools in Cluster 1, comparing fee-waiver applicants (Panel a) and non-fee-waiver applicants (Panel b). Cluster 1 schools apply a decentralized fee schedule, requiring students to pay application fees on a school-by-school basis (equation €120 per school). The dataset is restricted to individuals whose income is within a [-0.15; 0.15] relative distance from the fee waiver threshold, to focus the analysis on applicants near the eligibility cutoff.

Another way to observe the differentiated application behaviors of fee-paying candidates and fee-exempt candidates is to examine how the probability of applying to the most selective school in the cluster varies around the exemption threshold. Figure 12 and Table H8 indicate that the probability of applying to the most selective school in the cluster is significantly more reduced at the exemption threshold for schools with a decentralized application fee — 25 percentage points reduction, or a 45 percent decrease in the probability of applying to this school — compared to the most selective graduate school with a centralized application fee, for which the coefficient is not significant.

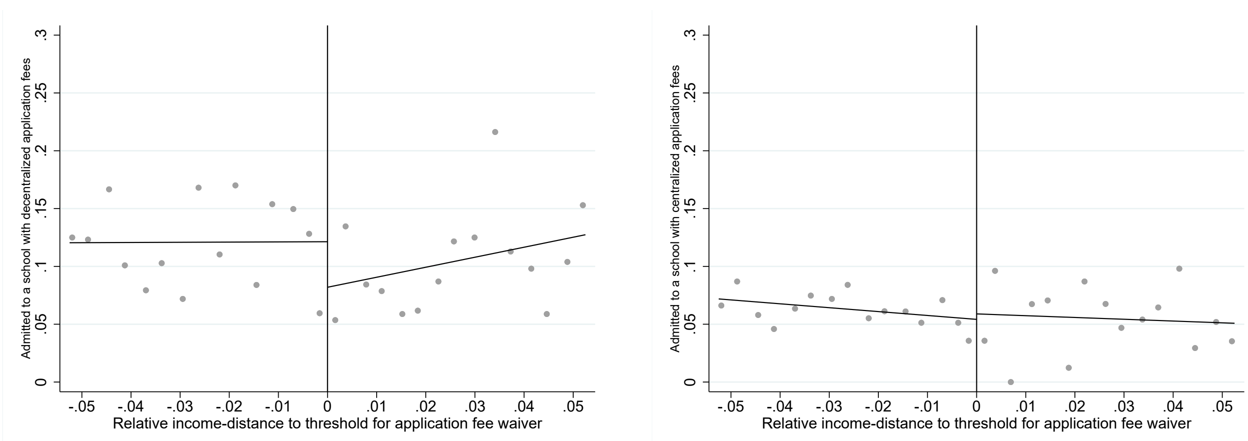
Figure 12: Impact of Application Fees on the Probability of Applying to the Most Selective Graduate School With Decentralized or Centralized Application Fees




(a) Cluster 1: Decentralized Application Fees (b) Cluster 2: Centralized Application Fees

*Notes:* The circles on the graph represent the proportion of candidates who apply to the most selective school in each cluster of schools as a function of the distance between their parental income and the application fee waiver threshold. This analysis is restricted to track 1, 2 and 3 aplicants, who are the one paying decentralized or centralized fees for those graduate schools. The solid lines in the graph show the estimated values obtained from a first-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold. School cluster 1 includes elite STEM graduate school with decentralized application fees for track 1, 2 and 3 students, while school cluster 2 includes elite STEM graduate school with centralized application fees for those students.

Figure 13: Probability of Admission to Graduate Schools with Decentralized or Centralized Application Fees




(a) Cluster 1: Decentralized Application Fees (b) Cluster 2: Centralized Application Fees

*Notes:* The circles on the graph represent the proportion of applicants admitted to Cluster 1 and Cluster 2 graduate schools based on the distance between their parental income and the application fee waiver threshold. Panel a shows the probability of admission to Cluster 1 schools for Tracks 1, 2 and 3 applicants, those paying decentralized application fees at Cluster 1 schools. Panel b shows the probability of admission to Cluster 2 schools for Track 1, 2 and 3 applicants. The solid lines in the graph show the estimated values obtained from a first-order polynomial approximation, estimated separately for the two sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold. School Cluster 1 includes elite STEM colleges with decentralized application fees for tracks 1, 2 and 3, while school Cluster 2 includes elite STEM colleges with centralized application fees for those tracks.

Table 13: Probability of Admission to Graduate Schools with Centralized versus Decentralized Application Fees

| | (1) | (2) | (3) |
|---|---|---|---|
| School cluster | Cluster 1 | Cluster 2 | Cluster 1 |
| Tracks considered | Track 1, 2 & 3 | Track 1, 2 & 3 | Track 4 |
| Application Fees | Decentralized | Centralized | Centralized |
| Baseline mean (fee-waiver students) | 0.13 | 0.07 | 0.03 |
| Baseline RD estimate | -0.071* | 0.004 | 0.095 |
| | (0.042) | (0.033) | (0.095) |
| Robust 95% CI | [-0.154 ; 0.011] | [-0.060 ; 0.069] | [-0.091 ; 0.282] |
| Obs. used in estimation | 2,853 | 2,713 | 370 |
| Total number of obs. | 8,102 | 8,102 | 1,205 |

*Notes:* The table reports estimated discontinuities in admission outcomes, by school cluster and track, around the application fee waiver threshold. Cluster 1 includes elite STEM graduate schools with decentralized application fees for tracks 1, 2 and 3 students and centralized application fees for track 4 students; while school Cluster 2 includes elite STEM graduate school with centralized application fees for all tracks. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

**Admission Outcomes.** Admission outcomes are less precisely estimated (Figure 13 and Table 13) due to the low number of individuals concerned. However, at the exemption threshold, the probability of admission is significantly lower by 7.1 percentage points, a 55 percent reduction, for schools with decentralized fee schedules. This contrasts with schools having centralized fee schedules, where admission probability changes are exactly zero at the threshold. Track 4 students, who pay centralized fees for Cluster 1 schools, show no different admission probability, although the results are not precisely estimated due to a small sample size. Table I9 suggests that the reduced admission probability is driven by the less selective schools within the cluster (a decrease of 7 to 8 percentage points in admission probability). The more selective school within the cluster also shows a decrease, although this result is not statistically significant, possibly due to the small sample size. Other top-tier schools in this cluster do not exhibit a different probability of admission at the threshold.

# 7 Discussion

As discussed earlier in the empirical strategy section, the need-based grant status also confers eligibility for a tuition fee waiver, but only at public institutions. In this section, I use variation in the amount of the tuition fee waiver at the eligibility threshold to check whether the results are influenced by anticipated tuition fees rather than application fees. I then perform a back-of-the-envelope calculation using the variation in both tuition and application fees at the threshold to compare students' sensitivity to application fees versus tuition fees.

## 7.1 Are Results Driven by Tuition Fee Waivers?

Figure I9 presents the distribution of tuition fees at public (Panel a) and private (Panel b) STEM graduate schools. On average, public schools cost 1,000 euros per year, with the vast majority charging 601 euros and a few selected ones charging up to 3,500 euros. Private graduate schools are significantly more expensive, with an average tuition of 7,500 euros, and some programs charging up to 10,000 euros during the study period (all amounts are in 2021 euros). It is important to note that (i) only public institutions grant tuition fee waivers for need-based grant students, and (ii) some public institutions with fees above the minimum of 601 euros offer partial waivers for individuals near the eligibility threshold (individuals on the right side of my regression discontinuity).[37]

The first test to determine whether students react to tuition fee waiver is to observe if the amount of tuition fees in the application set varies discontinuously at the threshold. Table P16 and Figure J10 show that fee-paying students tend to apply to graduate schools with a slightly lower sticker price (-224 euros or a 15 percent reduction from a baseline of 1,477 euros). However, this trend is entirely attributable to their applications to private schools, which are the most expensive. When focusing on the sticker price of public graduate schools (Column 2 of Table P16 and Panel (b) of Figure J10), no significant difference is observed in the sticker price

[37] Examples of public graduate schools granting these extra exemptions include *ESPCI*, *IMT Atlantique*, *IMT Lille Douai*, *IMT Mines d'Alès*, *Mines d'Albi*, *Mines de Paris*, *Mines Saint-Étienne*, *Télécom ParisTech*, *Télécom SudParis*, etc.

of applications between fee waiver and fee-paying candidates. This is consistent with a limited influence of tuition fee waivers on students' application behavior. For graduate schools where the threshold also determines tuition fee waiver eligibility, there is no difference in the average sticker price of applications, suggesting that the results described below are driven by application fees rather than anticipated tuition fee sensitivity. Columns (3) and (4) of Table P16 further reveal that there are no significant differences in the average sticker tuition price of the school of admission. Although the coefficient for all graduate schools is negative (-357 euros, a 17 percent reduction), the coefficient excluding private schools is very close to zero.

Since the amount of tuition fees of all public and private applications varies slightly, Table Q17 presents a robustness test of the main results, controlling for the average amount of tuition fees of the set of applications. This is to ensure that differences in application fees targeted by students are not driving the results. Overall, the findings are quite similar to the main estimates.

Another way to assess the consideration of tuition fees in application decisions is to observe how the tuition gain of the set of applications and the set of admissions varies at the threshold. This gain is defined as the difference between the sticker price and the price paid by fee waiver students.[38] If students heavily considered tuition fees in their application decisions, we would observe a significant drop in this gain at the eligibility threshold between fee waiver and fee-paying candidates (with fee-paying students applying to schools with much less gain than fee waiver students, since they do not benefit from this gain). Table R18 displays the amount of gain for application and admission to graduate schools. Overall, the coefficients are small, and this gain does not vary significantly at the eligibility threshold, reinforcing the view that students do not heavily consider tuition fees when making their application decisions.

In addition to the average gain, I also observe how the number of applications varies by tuition fee gain in Table S19. Fee-paying students decrease their applications to both public schools (Column 1) and private ones (Column 2). In relative terms, they reduce their applications to private schools more (63 percent reduction) compared to public graduate schools (26

[38]This gain is zero for the vast majority of private schools and equals the full sticker price for the majority of public schools, with some exceptions: private schools granting a partial fee waiver of 15 percent for low-income students, or public schools granting a partial fee waiver of 50 percent for non-eligible students at the margin of eligibility. Details on the amounts paid by fee waiver and fee-paying students were gathered from each graduate school's website or by directly contacting the graduate schools.

percent reduction). Since private schools only implement application fee waivers and not tuition fee waivers, this reduction can solely be attributed to the presence of application fees. If students were adjusting their application sets based on tuition fees, we would expect to see a greater reduction in applications to schools with the highest tuition fee gain (where being eligible for a fee waiver grants some advantage). However, this does not entirely appear to be the case, as their reduction in applications exhibits a U-shaped pattern with tuition gain: 64 percent reduction for the 1st quartile of gain (schools with no gain), 29 percent reduction for the 2nd quartile of gain (mostly inexpensive public schools), 21 percent reduction for the 3rd quartile of gain (more expensive public schools), and 31 percent reduction for the 4th quartile of gain (most expensive public schools).

As students reduction in application exhibit a U-shaped pattern with tuition fee gain (Table S19), I further verify that the results regarding the reduction in admission probability at the application fee waiver threshold are not driven by graduate schools with the highest tuition fee gain in Table T20, progressively excluding schools with the highest tuition fee gain in Columns 2, 3, and 4. The results are less precisely estimated than in the full sample and thus not significant, but they are of the same order of magnitude as the main estimates displayed in Column 1. In relative terms, the reduction in admission probability is actually very large when excluding all schools for which there is a tuition fee gain (in Column 4, a 33 percent reduction).

This rather myopic behavior among students could be explained by several factors: (i) students being on the edge of fee waiver eligibility, which could result in some losing the waiver in subsequent years due to a rise in parental income (about 30 percent of them lose the waiver from one year to the next), (ii) the low variance in fees at public STEM graduate schools, where most programs charge €601 per year, and (iii) the most expensive public programs generally offer partial tuition fee exemptions to individuals close to the waiver eligibility threshold.

### 7.2 Sensitivity of Students To Application Fees *vs* Tuition Fees

Are students more sensitive to application fees than to tuition fees? Variations in both the application fees paid and the tuition fees paid at the need-based grant threshold allow for an assessment of student sensitivities to these different costs, by computing admission-elasticities to the amount of application fees and enrollment-elasticities to the amount of tuition fees.

Table U21 displays the relevant admission and enrollment outcomes to observe sensitivity to application and tuition fees. Overall, there is a reduction of 11.3 percentage points (p.p.) in the probability of receiving an admission offer at the need-based grant threshold (a 14.5% reduction); a reduction of 11.8 p.p. in the probability of accepting an admission offer (a 19% reduction); and a reduction of 15.4 p.p. in the probability of enrolling in a STEM graduate school the following academic year (a 24.8% reduction). Column 4 of TableU21 shows the probability of enrollment, conditional on receiving any admission offer from a STEM graduate school in the centralized admission process. This coefficient is not significant but equals 9.3 p.p., representing a 12.4 percent reduction from a baseline enrollment probability of 75 percent for those who received an admission offer. One could argue that since students on both sides of the threshold do not receive an equal number of offers, their likelihood of accepting them might not be comparable. Nevertheless, it is important to note that, conditional on receiving an offer, there is no significant difference in the selectivity of the offers (Figure 9), suggesting that these graduate schools should be equally attractive to students.

To what variation in costs does this variation in admission/enrollment correspond? Table V22 shows the variation in the amounts of application fees and tuition fees paid at the need-based grant threshold. On average, the amount of application fees paid varies by €823 at the threshold (Column 1), and the amount of tuition fees paid for the school of admission, by €575 (see Figure K11 for the reduced form of these amounts). Importantly, the amount of theoretical tuition fees, meaning the sticker price of STEM graduate programs for which students receive an admission offer, does not significantly vary at the threshold.

Overall, these variations in amounts of application fees and tuition fees paid suggest that €823 in application fees reduces the probability of receiving an admission offer to any STEM graduate school by 14.5 percent, meaning that €1 of application fee reduces the probability to receive an admission offer by 0.0176%. €575 of first-year tuition fees reduces the probability to be enrolled by 12.4 percent, meaning €1 of first-year tuition fees reduces enrollment by 0.0216%. This accounts only for first-year tuition fees; if we consider the full STEM graduate program tuition fees for three years, with a 5% discount rate, €2,218[39] in full program tuition

[39] $1644 = 575 + \frac{575}{1.05} + \frac{575}{(1.05)^2}$

fees decreases enrollment by 12.4 percent, meaning €1 of tuition fees decreases enrollment by 0.0075 percent.

Overall, this suggests that applicants could be 0.8 times ($\frac{0.0176}{0.0216} = 0.8$) to 2.3 times ($\frac{0.0176}{0.0075} = 2.3$) more sensitive to application fees than to tuition fees. This tends to suggest that the sensitivity to application fees and to tuition fees is quite similar.

# 8 Concluding Remarks

In this study, I employ a regression discontinuity design to examine the impact of application fees on the application behaviors, admission outcomes, and enrollment of STEM graduate school applicants. My findings indicate that individuals subject to application fees submit fewer applications, leading to a reduced probability of admission. Furthermore, decentralized fee structures — where fees are paid to each school individually — exacerbate these effects compared to centralized schemes, where a single fee applies to multiple applications. Importantly, for those who do receive an offer, the selectivity of the admitted school remains unchanged.

Consistent with admission results, fee-paying candidates are less likely to enroll in STEM graduate schools in the three academic years following entrance exams to elite STEM programs but are more often enrolled in university programs. On average, they enroll in programs that are as selective: even though more often enrolled in university programs, less selective; they opt for more selective STEM graduate schools when they do. Using aggregated earning data, the expected earnings of the programs in which students enroll seem unaffected, though more detailed labor market data on longer career trajectories could provide more definitive insights.

A deeper analysis reveals distinct responses based on gender, socio-economic status (SES), and academic achievement: males, low-SES, and low-achieving applicants are more adversely affected by these fees in terms of application and admission outcomes. The observed gender heterogeneity primarily results from males reducing their *safety choices* and females reducing their *ambitious choices*. Aligned with this, in the following academic year, men are less likely to be enrolled in higher education, and women are enrolled in less selective programs, but these disparities disappear in subsequent academic years.

These results seem to be driven by application fees rather than anticipated tuition fees, as both fee-paying and fee waiver candidates apply to equally expensive public graduate schools. Additionally, students appear to be more sensitive to application fees than to tuition fees, considering the full program tuition fees.

Although students not admitted to STEM graduate schools can enroll in other programs that are equally selective and seem to offer similar labor market prospects, counterfactual simulations suggest that the removal of the fee waiver would result in lower representation of low-income students in STEM graduate schools, particularly in the most selective ones. This is a significant concern, given that they are already underrepresented in such selective programs, comprising only 26 percent of enrollees, despite representing more than 35 percent of all students. Nevertheless, the results also suggest that application fee waivers cause students to enroll much more frequently in private STEM graduate schools, which charge very high tuition fees even for low-income students, and that they could gain admission to equally selective university programs, which calls for a cautious assessment of the welfare effect of application fees.

It is important to recognize that the student population in this study is highly selected, consisting predominantly of individuals with high socio-economic status (SES) and high achievement levels, who are capable of making very informed decisions regarding higher education. Consequently, the results may not be generalizable to a broader student population. Additionally, it is essential to consider that the regression discontinuity design provides a local average treatment effect, which offers limited insights into the treatment effects at other points in the income distribution. The observed lack of effect on subsequent enrollment and the selectivity of the programs may also be attributable to the fee waiver being set at an optimal point in the parental income distribution, where individuals are sufficiently informed and capable of transitioning to equally selective programs. Further research in various contexts is necessary to more conclusively determine the impact of application fees on students' application choices, admission, enrollment outcomes, and labor market prospects, using detailed individual data across career trajectories.

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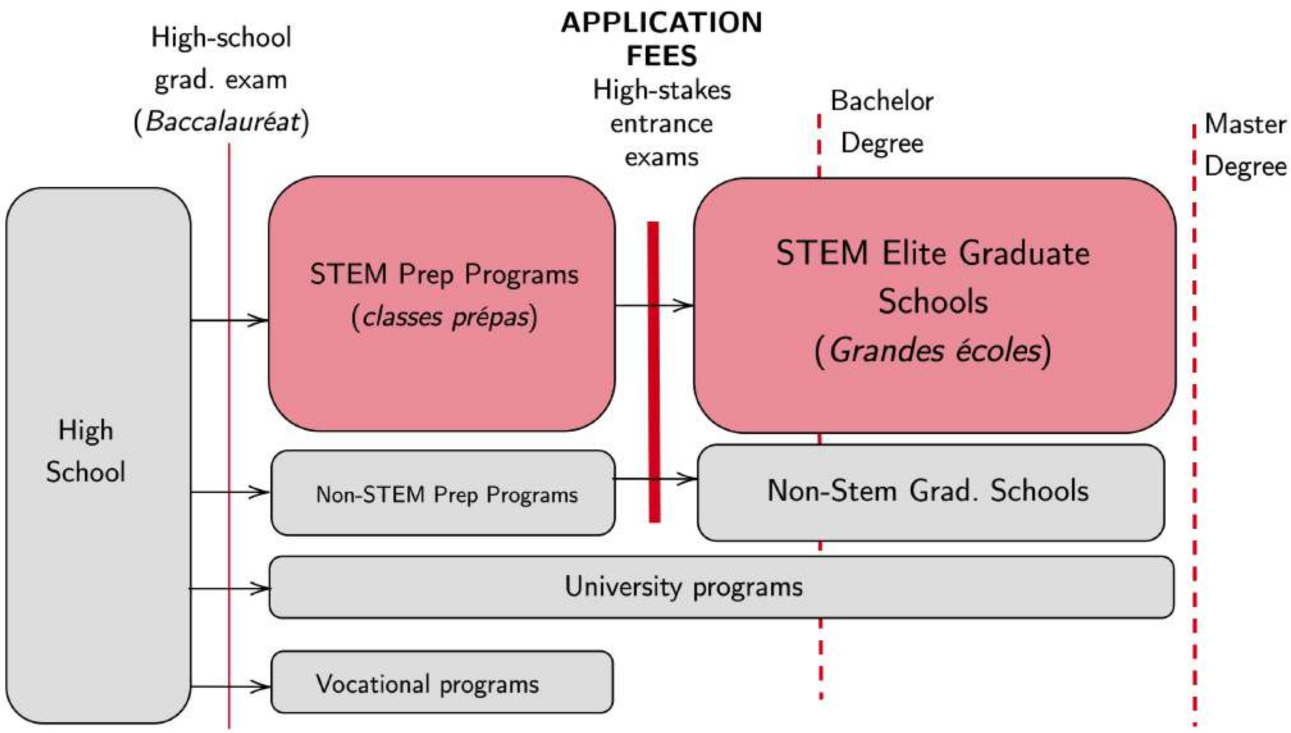
# Appendix

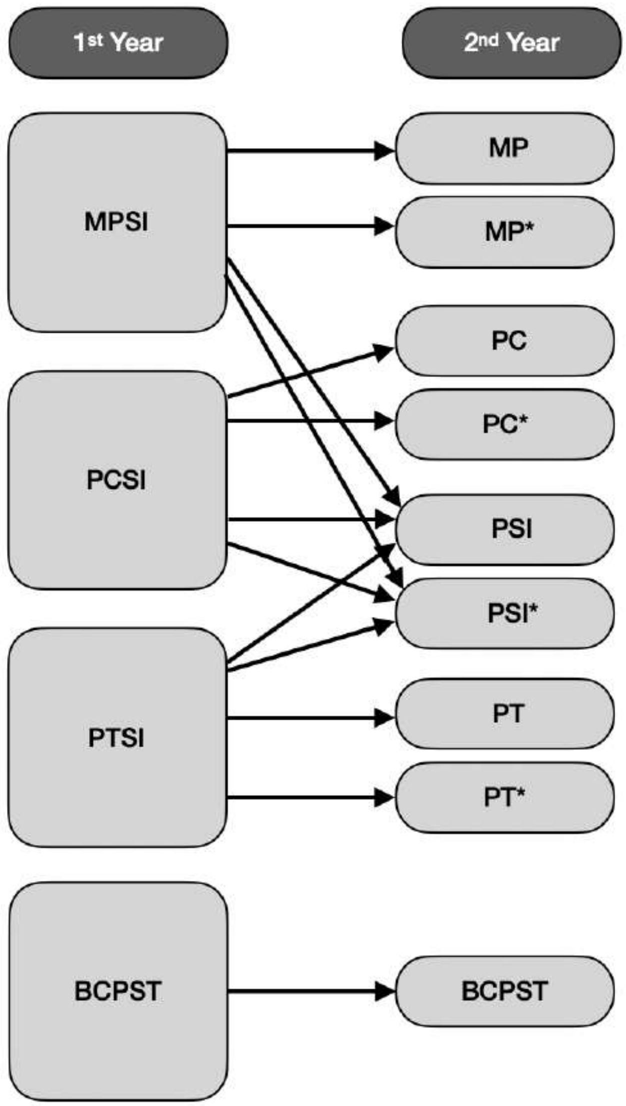
## A.1 Detailed Institutional Background

Figure A1: Organization Chart of STEM CPGE Programs



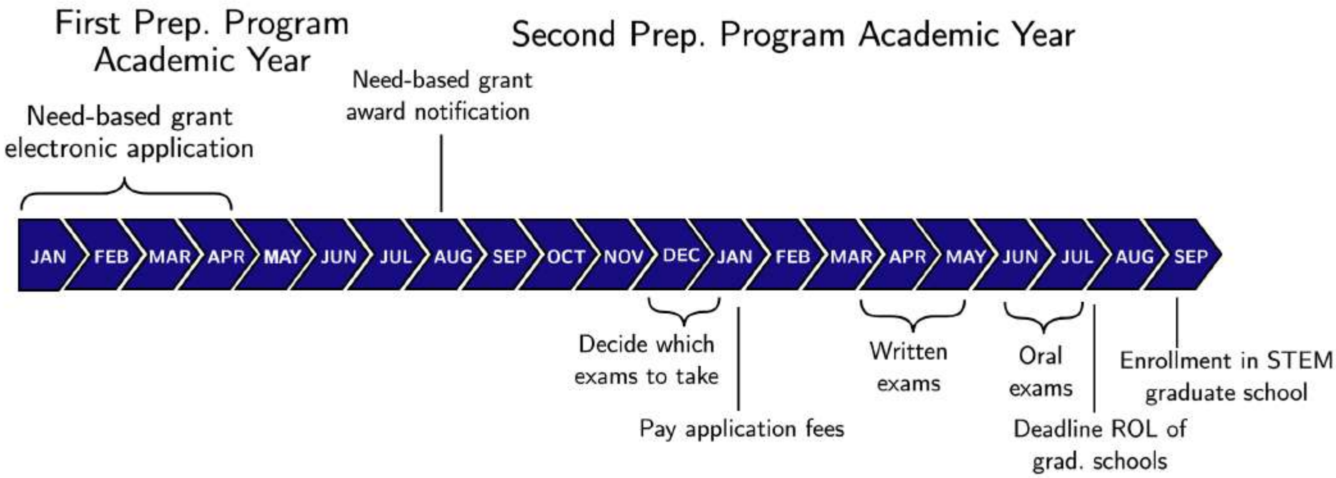

*Notes:* This diagram illustrates the structure of France's principal higher education pathways. The focus of this study, STEM preparatory programs and elite STEM graduate schools, are highlighted in red. Sections where application fees apply are marked with a prominent red bar.

Figure B2: Organization Chart of STEM Prep Programs



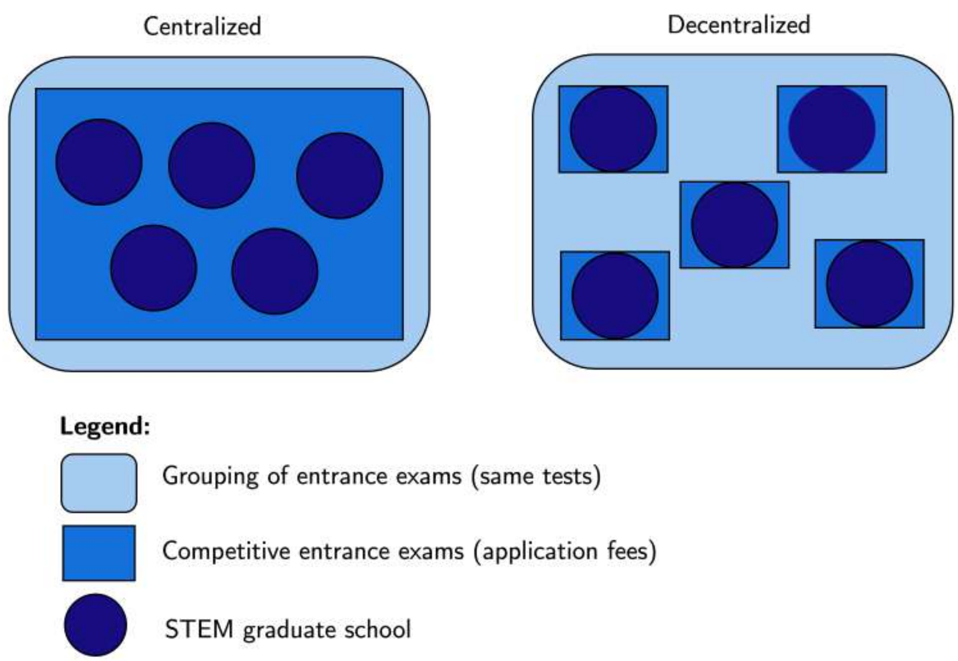

*Notes:* This diagram illustrates the various tracks available in STEM prep programs. MPSI/MP tracks are math-physics intensive, PCSI/PC tracks focus on physics-chemistry, PTSI/PSI/PT tracks are engineering science intensive, and BCPST tracks specialize in biology. For all tracks except the biology class, students are grouped by ability into 'star' classes for the highest-performing students and 'standard' classes for others in the second year of the program.

Figure C3: Schedule of Competitive Entrance Exams to Elite STEM Graduate Schools




*Notes:* This diagram illustrates the schedule of the application fee waiver process over two academic years in the prep program. To be eligible for the fee waiver, which is contingent upon obtaining need-based grant status, students must apply for need-based grants during the first year of the program. They decide which exams to take in January of the second academic year. The exams are administered between April and July, with the first admission results announced by the end of July.

Figure D4: Diagram of Entrance Exams Structure



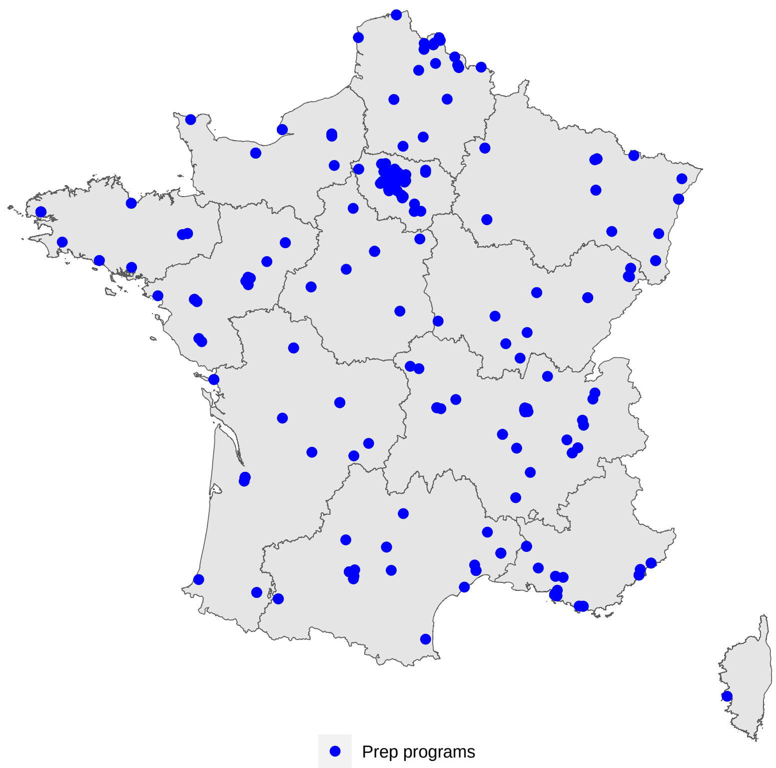

*Notes:* This diagram simplifies the organization of high-stakes entrance exams. Entrance exams are grouped into clusters, while this is still the layer of competitive entrance exams charging application fees and potentially leading to admission into one or more graduate schools.

Table A1: Design of Application Fees

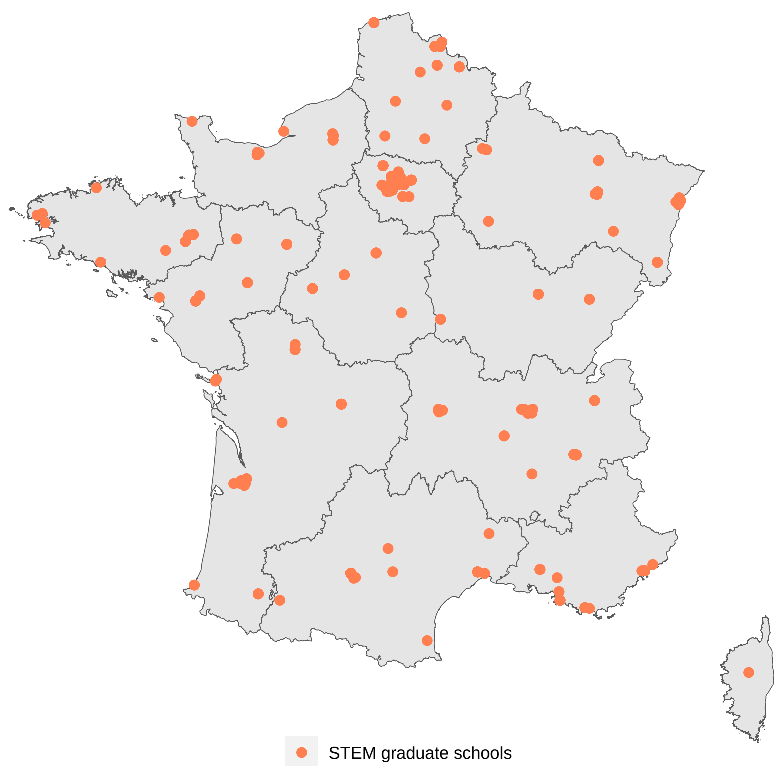
| | Track 1, 2 & 3 | | Track 4 | |
|---|---|---|---|---|
| | Graduate School | Application Fees | Graduate School | Application Fees |
| | School 1A | €120 | School 1A | |
| | School 1B | €120 | School 1B | |
| Cluster 1 | School 1C | €120 | School 1C | €180 |
| | School 1D | €120 | School 1D | |
| | School 1E | €120 | School 1E | |
| | School 2A | | School 2A | |
| | School 2B | | School 2B | |
| Cluster 2 | School 2C | €320 | School 2C | €320 |
| | School 2D | | School 2D | |
| | School 2E | | School 2E | |

*Notes:* This table shows the application fee design for Cluster 1 (*Banque Centrale*) and Cluster 2 (*Banque Mines Ponts*) graduate schools. For Cluster 1 schools, Track 1, 2 and 3 applicants pay a decentralized application fee: they pay 120 euros for each school they wish to apply to. For the same cluster of schools, Track 4 applicants pay a centralized application fee: they pay 180 euros to apply to all schools in the cluster. For Cluster 2 schools, all applicants pay a centralized application fee of 320 euros.

Figure E5: Location of STEM Prep Programs and Graduate Schools




(a) STEM Prep Programs




(b) STEM Graduate Schools

*Notes:* These maps display the location of prep programs (panel a) and STEM graduate schools (panel b) in metropolitan France.

Figure F6: Extract of Application Fees for Track 1 (MP) in 2020

| Banque Centrale-Supélec | Frais de dossier | |
|---|---|---|
| | Non Boursier | Boursier * |
| CentraleSupélec | 170,00 € | - |
| CentraleSupélec Etranger | 170,00 € | - |
| CentraleSupélec + CentraleSupélec Etranger | 255,00 € | - |
| Centrale Lyon | 110,00 € | - |
| Institut d'Optique Graduate School (SupOptique) | 110,00 € | - |
| Institut d'Optique Graduate School (SupOptique) étranger | 110,00 € | - |
| Institut d'Optique Graduate School (SupOptique) + SupOptique étranger | 165,00 € | - |
| Centrale Lille | 110,00 € | - |
| Centrale Nantes | 110,00 € | - |
| Centrale Marseille | 110,00 € | - |
| Centrale Casablanca | 110,00 € | - |
| Centrale Casablanca via CNC | - | - |
| Arts et Métiers / ENSEA Cergy | 135,00 € | - |
| UTT Université de Technologie de Troyes | 110,00 € | 10,00 € |
| EPF Sceaux - Troyes - Montpellier | 80,00 € | 10,00 € |
| ESTP | 75,00 € | 15,00 € |
| École Navale Brest | - | - |

** Les candidats pupilles de l'Etat ou pupilles de la nation doivent acquitter les frais de dossier au tarif des candidats boursiers*

| Banque Mines Ponts | Frais de dossier | |
|---|---|---|
| | Non Boursier | Boursier |
| Concours Commun Mines Ponts (1) | 320,00 € | - |
| Concours Mines - Télécom (2) | 285,00 € | - |
| Concours Commun TPE / EIVP (3) | 40,00 € | - |
| Cycle International Centrale-Supélec (4) | 230,00 € | - |

(1) Ponts ParisTech, ISAE - SUPAERO, ENSTA Paris, Télécom Paris-(cursus Paris et Sophia Antipolis), Mines Paris, Mines St-Etienne, Mines Nancy, IMT Atlantique (cursus Brest-Nantes et Sophia Antipolis), ENSAE Paris, Chimie ParisTech.

(2) IMT Mines Albi, IMT Mines Alès, IMT Lille - Douai, ENSTA Bretagne (filière sous statut étudiant), ENSG Géologie ENSTA Bretagne (filière sous statut IETA - Direction Générale de l'Armement), Télécom SudParis - cursus Evry et cursus Sophia, Mines St-Etienne-ISMIN, Télécom Saint-Etienne (statut étudiant), Télécom Saint-Etienne (statut apprenti), ENSG-Géomatique (civil), Télécom Nancy, ENSSAT Lannion, Télécom Physique Strasbourg -TI-Santé, Télécom Physique Strasbourg - Réseaux et Télécoms, ENSIIE Evry.

(3) Concours Commun TPE : ENTPE, ENM, ENSG Marne la Vallée (fonctionnaire), Mines Douai (fonctionnaire) - Concours EIVP.

(4) Réservé aux candidats étrangers ayant suivi leur scolarité en Côte d'Ivoire, au Liban, en Tunisie, au Maroc, au Gabon, en Mauritanie et au Cameroun.

*Notes:* This table shows the application fees for Track 1 (MP) candidates applying to the Cluster 1 (*Centrale Supélec*) and Cluster 2 (*Mines Ponts*) schools. The complete application fees for Track 1 students in 2021 can be found at this link.

## B.2 Proofs of the Conceptual Framework

### B.2.1 Proof of Proposition 1

I will use a generic utility function $u : [0, T] \to \mathbb{R}_+$, assumed strictly increasing, to prove the results for both risk-neutral (taking $u(x) = x$) and risk-averse students (taking $u(x) = \sqrt{x}$).

*Case 1.* Students prefer strategy 1 (1,1) to strategy 4 (0,0).

$$\begin{aligned} U_{(1,1)} - U_{(0,0)} &= p_1 u(x_1) + p_2(1-p_1)u(x_2) + (1-p_1)(1-p_2)u(x_0) - u(x_0) \\ &= p_1 u(x_1) + p_2 u(x_2) - p_1 p_2 u(x_2) + (p_1 p_2 - p_1 - p_2)u(x_0) \\ &= p_1(u(x_1) - u(x_0)) + p_2(u(x_2) - u(x_0)) - p_1 p_2(u(x_2) - u(x_0)) \\ &= p_1(u(x_1) - u(x_0)) + p_2(1-p_1)(u(x_2) - u(x_0)) \end{aligned}$$

As $x_1 > x_0$ and $u$ is increasing, $u(x_1) > u(x_0)$. As $x_2 > x_0$ and $u$ is increasing, $u(x_2) > u(x_0)$. Since $0 < p_1 < p_2 < 1$, the equation is the sum of two positive terms and is therefore positive. Consequently, $U_{(1,1)} > U_{(0,0)}$.

*Case 2.* Students prefer strategy 1 (1,1) to strategy 2 (1,0).

$$\begin{aligned} U_{(1,1)} - U_{(1,0)} &= p_1 u(x_1) + p_2(1-p_1)u(x_2) + (1-p_1)(1-p_2)u(x_0) - p_1 u(x_1) - (1-p_1)u(x_0) \\ &= p_2(1-p_1)u(x_2) + (1-p_1)(1-p_2)u(x_0) - (1-p_1)u(x_0) \\ &= p_2(1-p_1)u(x_2) - (1-p_1)p_2 u(x_0) \\ &= (1-p_1)p_2(u(x_2) - u(x_0)) \end{aligned}$$

Since $u(x_2) > u(x_0)$ and $(1-p_1)p_2 > 0$, the expression is positive. Therefore, $U_{(1,1)} > U_{(1,0)}$.

*Case 3.* Students prefer strategy 1 (1,1) to strategy 3 (0,1).

$$
\begin{aligned}
U_{(1,1)} - U_{(0,1)} &= p_1 u(x_1) + p_2(1-p_1)u(x_2) + (1-p_1)(1-p_2)u(x_0) - p_2 u(x_2) - (1-p_2)u(x_0) \\
&= p_1 u(x_1) - p_1 p_2 u(x_2) + (1-p_2)(1-p_1-1)u(x_0) \\
&= p_1 u(x_1) - p_1 p_2 u(x_2) - p_1(1-p_2)u(x_0) \\
&= p_1(u(x_1) - u(x_0)) - p_1 p_2(u(x_2) - u(x_0))
\end{aligned}
$$

With $u(x_1) > u(x_2)$, thus $u(x_1) - u(x_0) > u(x_2) - u(x_0)$, and since $p_1 > p_1 p_2$, the expression $p_1(u(x_1) - u(x_0)) > p_1 p_2(u(x_2) - u(x_0))$ holds. Therefore, the overall expression is positive, confirming that $U_{(1,1)} > U_{(0,1)}$.

*Conclusion.* Both risk-averse ($u^A(x) = \sqrt{x}$) and risk-neutral students ($u^N(x) = x$) prefer to apply to both graduate schools 1 and 2 when they do not pay application fees ($W$). ■

### B.2.2 Proof of Proposition 2

I first show under which condition students prefer the application strategy (1,0) (i.e. apply only to the most selective graduate school) over the application strategy (0,1) (i.e. apply only to the less selective graduate school).

$$
\begin{aligned}
U_{(1,0)} - U_{(0,1)} &= p_1 u(x_1) + (1-p_1)u(x_0) - f - (p_2 u(x_2) + (1-p_2)u(x_0) - f) \\
&= p_1 u(x_1) - p_2 u(x_2) + (1-p_1)u(x_0) - (1-p_2)u(x_0) \\
&= p_1(u(x_1) - u(x_0)) - p_2(u(x_2) - u(x_0))
\end{aligned}
$$

This equation is positive if and only if:

$$
\begin{aligned}
p_1(u(x_1) - u(x_0)) &> p_2(u(x_2) - u(x_0)) \\
\iff \frac{u(x_1) - u(x_0)}{u(x_2) - u(x_0)} &> \frac{p_2}{p_1}
\end{aligned}
$$

So if $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} > \frac{p_2}{p_1}$, students prefer to apply to the most selective graduate school (1,0) instead of the less selective graduate school (0,1). Conversely, the reverse holds if $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} <$

$\frac{p_2}{p_1}$. Note that this holds for any amount of application fees, as the application fee to graduate school 1 and 2 is the same.

I now identify under which conditions students prefer to apply to both graduate schools (1,1) compared to one school (1,0) or (0,1):

- If $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} > \frac{p_2}{p_1}$, the trade-off is between (1,1) and (1,0):

$$\begin{aligned} U_{(1,1)} - U_{(1,0)} &= p_1 u(x_1) + p_2(1-p_1)u(x_2) + (1-p_1)(1-p_2)u(x_0) - 2f \\ &\quad - (p_1 u(x_1) + (1-p_1)u(x_0) - f) > 0 \\ &\iff (1-p_1)p_2 u(x_2) - p_2(1-p_1)u(x_0) - f > 0 \\ &\iff (1-p_1)p_2(u(x_2) - u(x_0)) > f \end{aligned}$$

  Note that in this case, $\min((1-p_1)p_2(u(x_2)-u(x_0)), p_1(u(x_1)-u(x_0)) - p_1 p_2(u(x_2)-u(x_0))) = (1-p_1)p_2(u(x_2)-u(x_0))$.

- If $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} < \frac{p_2}{p_1}$, the trade-off is between (1,1) and (0,1):

$$\begin{aligned} U_{(1,1)} - U_{(0,1)} &= p_1 u(x_1) + p_2(1-p_1)u(x_2) + (1-p_1)(1-p_2)u(x_0) - 2f \\ &\quad - (p_2 u(x_2) + (1-p_2)u(x_0) - f) > 0 \\ &\iff p_1 u(x_1) - p_1 p_2 u(x_2) - p_1(1-p_2)u(x_0) - f > 0 \\ &\iff p_1(u(x_1) - u(x_0)) - p_1 p_2(u(x_2) - u(x_0)) > f \end{aligned}$$

  Note that in this case, $\min((1-p_1)p_2(u(x_2)-u(x_0)), p_1(u(x_1)-u(x_0)) - p_1 p_2(u(x_2)-u(x_0))) = p_1(u(x_1)-u(x_0)) - p_1 p_2(u(x_2)-u(x_0))$.

- Thus, the optimal strategy for students is to choose (1,1), i.e., apply to both graduate schools instead of just one, if and only if $f < \min((1-p_1)p_2(u(x_2)-u(x_0)), p_1(u(x_1)-u(x_0)) - p_1 p_2(u(x_2)-u(x_0)))$.

Lastly, I identify under which conditions students prefer to apply to one school (1,0) or (0,1) compared to no graduate school (0,0):

- If $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} > \frac{p_2}{p_1}$, the trade-off is between (1,0) and (0,0):

$$U_{(1,0)} - U_{(0,0)} = p_1 u(x_1) + (1-p_1)u(x_0) - f - u(x_0) > 0$$

$$\iff p_1(u(x_1) - u(x_0)) > f$$

  Note that in this case, $\max(p_1(u(x_1) - u(x_0)), p_2(u(x_2) - u(x_0))) = p_1(u(x_1) - u(x_0))$.

- If $\frac{u(x_1)-u(x_0)}{u(x_2)-u(x_0)} < \frac{p_2}{p_1}$, the trade-off is between (0,1) and (0,0):

$$U_{(0,1)} - U_{(0,0)} = p_2 u(x_2) + (1-p_2)u(x_0) - f - u(x_0) > 0$$

$$\iff p_2(u(x_2) - u(x_0)) > f$$

  Note that in this case, $\max(p_1(u(x_1) - u(x_0)), p_2(u(x_2) - u(x_0))) = p_2(u(x_2) - u(x_0))$.

- Therefore, the optimal strategy for students is to choose (0,0), i.e., apply to no graduate school and opt for the outside option, if and only if $f > \max(p_1(u(x_1) - u(x_0)), p_2(u(x_2) - u(x_0)))$. ■

### B.2.3 Proof of Proposition 3

- Risk-neutral students switch from applying to the most selective graduate school (1,0) to the less selective one (0,1) when $\frac{x_1-x_0}{x_2-x_0} < \frac{p_2}{p_1}$. Risk-averse students make the switch when $\frac{\sqrt{x_1}-\sqrt{x_0}}{\sqrt{x_2}-\sqrt{x_0}} < \frac{p_2}{p_1}$.
  - Given that $x_1 > x_2 > x_0$, and the concavity of the square root function implies $\frac{\sqrt{x_1}-\sqrt{x_0}}{x_1-x_0} < \frac{\sqrt{x_2}-\sqrt{x_0}}{x_2-x_0}$, there are more values of the ratio $\frac{p_2}{p_1}$ where risk-averse students opt for the less selective school over the most selective one.

- Risk-neutral students switch from applying to both graduate schools to applying to only one graduate school when $f > \min((1-p_1)p_2(x_2-x_0), p_1(x_1-x_0) - p_1p_2(x_2-x_0))$. Call this amount $A$. Risk-averse students switch from applying to both graduate schools to applying to only one graduate school when $f > \min((1-p_1)p_2(\sqrt{x_2}-\sqrt{x_0}), p_1(\sqrt{x_1}-\sqrt{x_0}) - p_1p_2(\sqrt{x_2}-\sqrt{x_0}))$. Call this amount $A'$.

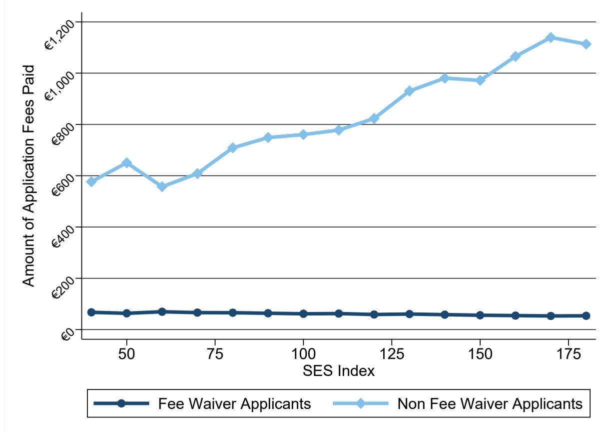
- When $x_0 > 1$, $(1 - p_1)p_2(\sqrt{x_2} - \sqrt{x_0}) < (1 - p_1)p_2(x_2 - x_0)$ and $p_1(\sqrt{x_1} - \sqrt{x_0}) - p_1p_2(\sqrt{x_2} - \sqrt{x_0}) < p_1(x_1 - x_0) - p_1p_2(x_2 - x_0)$, it follows that $A' < A$, and risk-averse students switch to applying to one graduate school instead of two for lower amounts of application fees $f$ than risk-neutral students.

- Risk-neutral students switch from applying to one graduate school to no graduate school when $f > \max(p_1(x_1 - x_0), p_2(x_2 - x_0))$. Call this amount $B$. Risk-averse students make the same switch when $f > \max(p_1(\sqrt{x_1} - \sqrt{x_0}), p_2(\sqrt{x_2} - \sqrt{x_0}))$. Call this amount $B'$.

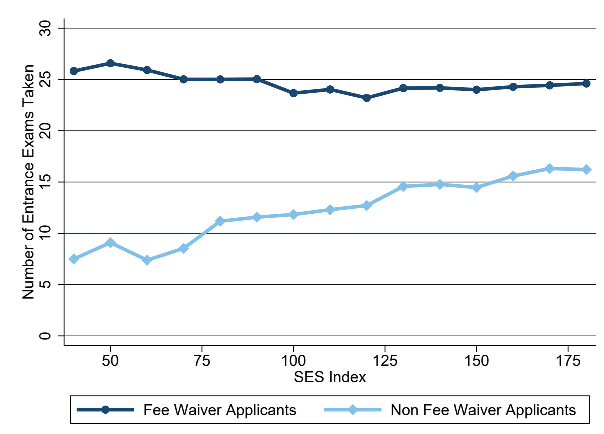
  - When $x_0 > 1$, $p_1(\sqrt{x_1} - \sqrt{x_0}) < p_1(x_1 - x_0)$ and $p_2(\sqrt{x_2} - \sqrt{x_0}) < p_2(x_2 - x_0)$, it follows that $B' < B$ and risk-averse students switch to applying to no graduate school for lower amounts of application fees $f$. ■

## C.3 Supplementary Figures

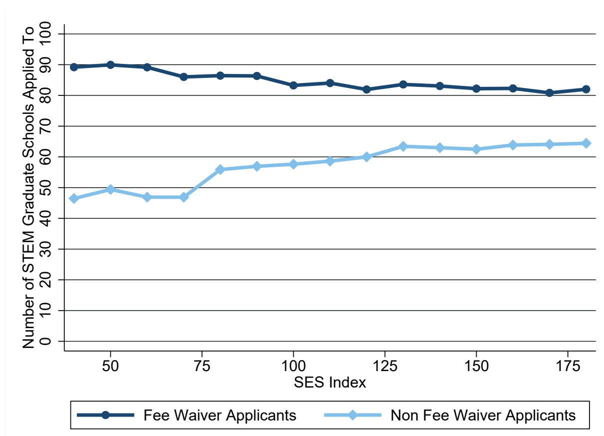
Figure G7: Application Fees and Number of Application by Fee Waiver Status and Socio-Economic Index




(a) Application Fees



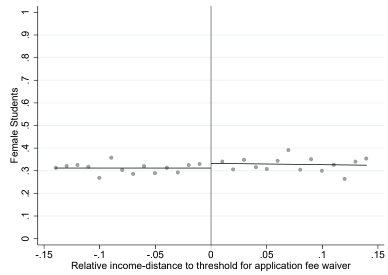

(b) Number of Exams Taken



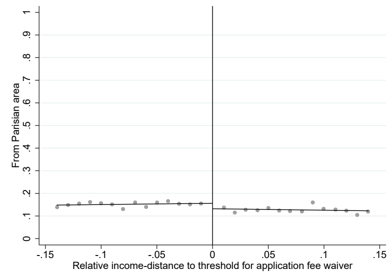

(c) Number of Grad. Schools Applied To

*Notes:* Panel a illustrates average application fees to elite STEM schools, segmented by the socio-economic status (SES) indices of applicants' parents and differentiated by fee waiver status. Panel b shows the average number of exams taken by applicants, categorized by SES indices and fee waiver status. Panel c displays the number of STEM graduate schools applied to, corresponding to the total schools eligible based on the entrance exams taken, irrespective of their inclusion in students' ranked preferences. The SES index, derived from the Department of Education's DEPP index (*Indice de Position Sociale*, IPS), combines two parental occupation categories, each disaggregated into 44 categories, into a single index, reflecting the economic and academic capital of the household. Fee waivers are allocated based on parental income, distance to the higher education program, and the number of siblings, including those in higher education. The data originates from the SCEI administrative datasets, spanning 2015-2023.

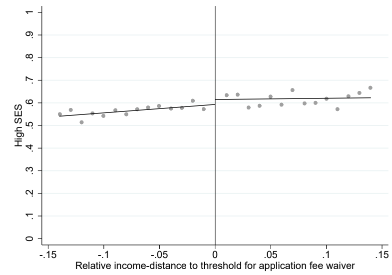
Figure H8: Balance of Applicants Characteristics Around Threshold



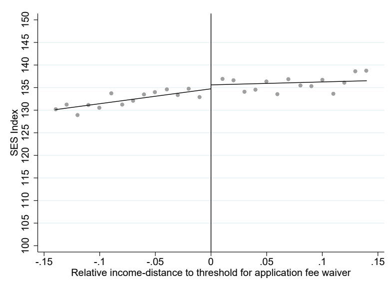

(a) Female students



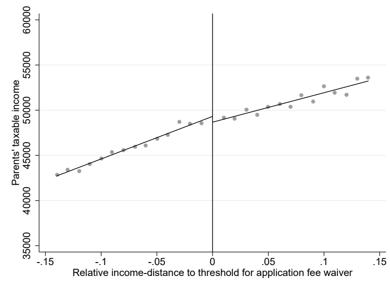

(b) From Parisian area



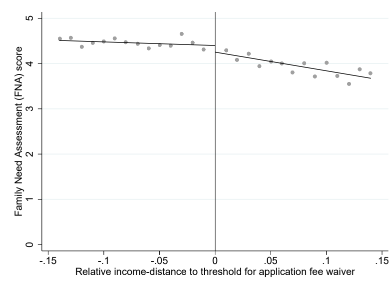

(c) High SES



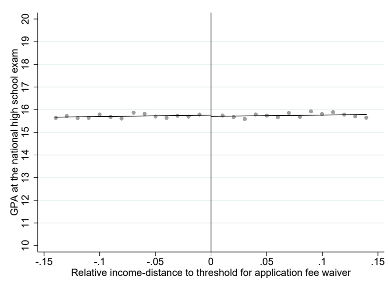

(d) SES Index



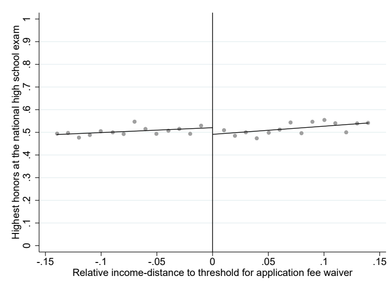

(e) Parents' Taxable Income



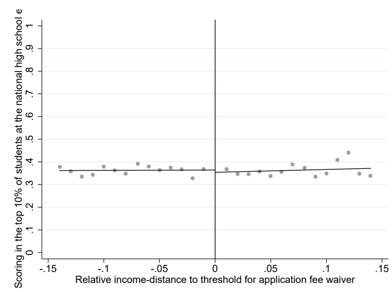

(f) Family Needs Assessment (FNA) Score



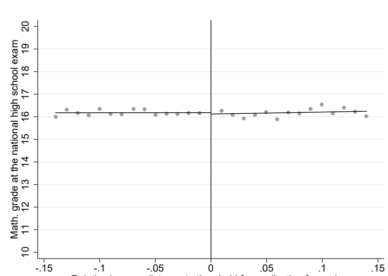

(g) GPA at the national high school exam



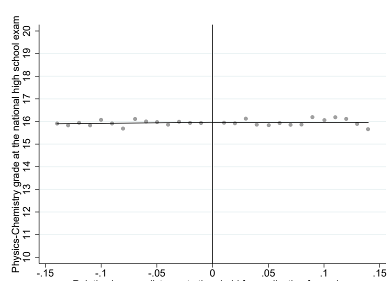

(h) Highest honors at the high school graduate exam



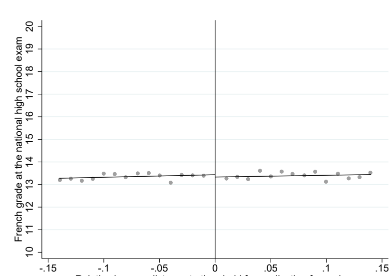

(i) Scoring in the top 10 percent of students at the national high school exam



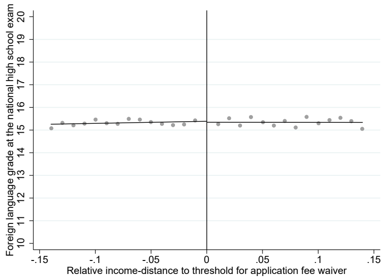

(j) Math. grade at the national high school exam



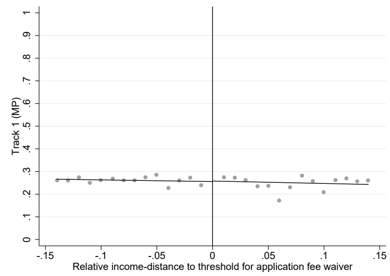

(k) Physics-Chemistry grade at the national high school exam



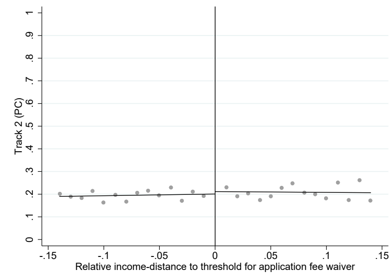

(l) French grade at the national high school exam



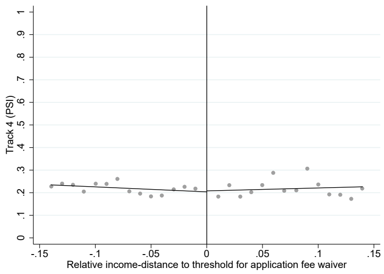

(m) Foreign language grade at the national high school exam



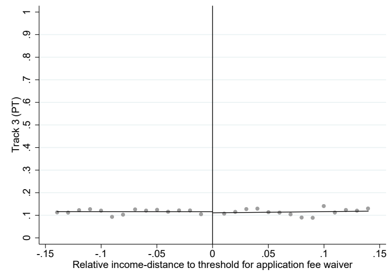

(n) Track 1 (MP)



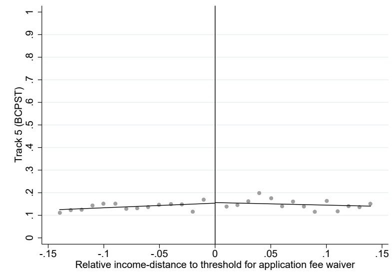

(o) Track 2 (PC)




(p) Track 3 (PSI)




(q) Track 4 (PT)




(r) Track 5 (BCPST)

*Notes:* The circles on the graph depict various observable characteristics, as a function of the distance between parental income and the application fee waiver threshold. The solid lines on the graph represent the estimated values obtained from a first-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver.

## D.4 Supplementary Tables

Table B2: Descriptive Statistics of the Full Sample

| | Sample | | |
|---|---|---|---|
| | All students (1) | Non fee waiver students (2) | Fee waiver students (3) |
| *Panel A. Demographic Characteristics* | | | |
| Need-based scholarship holder | 0.26 | 0.00 | 1.00 |
| Female student | 0.30 | 0.30 | 0.30 |
| From Paris | 0.06 | 0.07 | 0.04 |
| From Parisian area (outside Paris) | 0.18 | 0.19 | 0.16 |
| SES index | 137.89 | 144.97 | 117.92 |
| Father High SES | 0.59 | 0.69 | 0.28 |
| Father Medium High SES | 0.09 | 0.08 | 0.12 |
| Father Medium Low SES | 0.20 | 0.16 | 0.29 |
| Father Low SES | 0.08 | 0.04 | 0.18 |
| Mother High SES | 0.45 | 0.53 | 0.21 |
| Mother Medium High SES | 0.12 | 0.11 | 0.14 |
| Mother Medium Low SES | 0.23 | 0.18 | 0.37 |
| Mother Low SES | 0.11 | 0.10 | 0.15 |
| *Panel B. Previous Academic Achievement* | | | |
| *Baccalauréat* GPA | 15.67 | 15.82 | 15.33 |
| Highest honors at the *Baccalauréat* | 0.49 | 0.51 | 0.43 |
| Top 10% of students at the *Baccalauréat* | 0.28 | 0.28 | 0.29 |
| *Panel C. Prep Program Characteristics* | | | |
| Enrolled in star class (top track) | 0.25 | 0.26 | 0.21 |
| Prep program in Paris | 0.14 | 0.15 | 0.13 |
| Prep program in Parisian area (outside Paris) | 0.12 | 0.12 | 0.09 |
| Track 1 (MP) | 0.31 | 0.33 | 0.25 |
| Track 2 (PC) | 0.19 | 0.18 | 0.20 |
| Track 3 (PSI) | 0.21 | 0.21 | 0.21 |
| Track 4 (PT) | 0.09 | 0.09 | 0.10 |
| Track 5 (BCPST) | 0.11 | 0.11 | 0.13 |
| **Number of students** | 245,559 | 181,330 | 64,229 |

*Notes:* This table presents the descriptive statistics for all students registered in the prep program who took high-stakes entrance exams from 2015 to 2023. The statistics are provided for all students in Column 1, and the sample is subsequently divided between fee-waiver recipients in Column 2 and non-fee-waiver students in Column 3. Socioeconomic Status (SES) is categorized according to the classification system of the Ministry of National Education, using either a four-category scheme or the Index of Parental Socioeconomic Status (IPS), which aggregates both parents' occupations into a single metric. For comparative purposes, Table 1 presents these descriptive statistics for the reduced RD sample of individuals close to the fee waiver eligibility threshold (N=11,945).

Table C3: Compliers Characteristics: Probability To Be Fee Exempted

| | **Compliers** | | **Always** | **Never** |
|---|---|---|---|---|
| | **Treated** | **Untreated** | **Takers** | **Takers** |
| | Fee-waiver & Below threshold | Fee-paying & Above threshold | Fee-waiver & Above threshold | Fee-paying & Below threshold |
| *Panel A. Demographic Characteristics* | | | | |
| Female student | 0.315 | 0.333 | 0.344 | 0.295 |
| | (0.009) | (0.007) | (0.004) | (0.004) |
| From Paris | 0.025 | 0.025 | 0.033 | 0.025 |
| | (0.003) | (0.002) | (0.002) | (0.002) |
| From Parisian area | 0.115 | 0.088 | 0.148 | 0.126 |
| | (0.006) | (0.005) | (0.003) | (0.003) |
| SES index | 131.8 | 136.1 | 129.3 | 135.9 |
| | (0.5) | (0.4) | (0.3) | (0.3) |
| Father High SES | 0.412 | 0.474 | 0.475 | 0.475 |
| | (0.009) | (0.008) | (0.005) | (0.005) |
| Mother High SES | 0.317 | 0.361 | 0.311 | 0.381 |
| | (0.009) | (0.008) | (0.004) | (0.005) |
| *Panel B. Previous Academic Achievement* | | | | |
| *Baccalauréat* GPA | 15.77 | 15.80 | 15.67 | 15.47 |
| | (0.04) | (0.03) | (0.02) | (0.02) |
| Highest honors at the *Baccalauréat* | 0.518 | 0.529 | 0.475 | 0.440 |
| | (0.009) | (0.008) | (0.005) | (0.005) |
| Top 10% of students at the *Baccalauréat* | 0.373 | 0.373 | 0.367 | 0.311 |
| | (0.009) | (0.008) | (0.004) | (0.005) |
| *Panel C. Prep Program Characteristics* | | | | |
| Enrolled in star class (top track) | 0.251 | 0.248 | 0.246 | 0.237 |
| | (0.008) | (0.007) | (0.004) | (0.004) |
| Prep program in Paris | 0.090 | 0.078 | 0.066 | 0.095 |
| | (0.005) | (0.004) | (0.002) | (0.003) |
| Prep program in Parisian area (outside Paris) | 0.087 | 0.063 | 0.115 | 0.101 |
| | (0.005) | (0.004) | (0.003) | (0.003) |
| Track 1 (MP) | 0.264 | 0.251 | 0.262 | 0.252 |
| | (0.008) | (0.007) | (0.004) | (0.004) |
| Track 2 (PC) | 0.197 | 0.211 | 0.197 | 0.193 |
| | (0.007) | (0.006) | (0.004) | (0.004) |
| Track 3 (PSI) | 0.217 | 0.213 | 0.213 | 0.239 |
| | (0.008) | (0.007) | (0.004) | (0.004) |
| Track 4 (PT) | 0.113 | 0.114 | 0.066 | 0.126 |
| | (0.006) | (0.005) | (0.002) | (0.003) |
| Track 5 (BCPST) | 0.139 | 0.153 | 0.148 | 0.130 |
| | (0.006) | (0.006) | (0.003) | (0.003) |
| Share of sample | 0.700 | | 0.015 | 0.275 |
| N | | | | 11,945 |

*Notes:* This table reports on compliers, always takers, and never takers' characteristics using the procedure described in Abadie (2002, 2003); Angrist et al. (2023). Compliers are individuals who do pay application fees when above the eligibility threshold and who do not when below the threshold. Always takers are individuals who do not pay the fee even when above the eligibility threshold (this is very rare, around 1.5 percent of the sample), and never takers are individuals who do pay the application fee although below the eligibility threshold, probably due to a rise in parental income between the need-based grant application and taking the high-stakes entrance exams. Estimates from columns (1) and (2) are obtained by regressing the observable characteristic under consideration multiplied by the treatment status ($D_i$ in Column 1 and $(1-D_i)$ in Column (2), with $D_i = 1$ for fee waiver applicants) on the treatment status, instrumented by the fact of being below the eligibility threshold ($Z_i = 1$ for individuals below and $Z_i = 0$ for individuals above). Estimates in columns (3) for always takers are obtained through the regression of $X_iD_i(1-Z_i)$ on $D_i(1-Z_i)$. Estimates in columns (4) for never takers are obtained through the regression of $X_i(1-D_i)Z_i$ on $(1-D_i)Z_i$. This is equivalent to computing the mean of the observable characteristics $X_i$ for individuals with $D_i = 1$ and $Z_i = 0$ (always-takers) and for individuals with $D_i = 0$ and $Z_i = 1$ (never-takers).

Table D4: Rddensity Test, Assuming Different CDF and Bandwidth

| | Bw_Left | Bw_Rigth | NObs_Left | NObs_Right | p_value |
|---|---|---|---|---|---|
| Equal cdf - Symmetric bw | 0.018 | 0.018 | 921 | 661 | 0.210 |
| Not equal cdf - Symmetric bw | 0.013 | 0.013 | 687 | 504 | 0.303 |
| Not equal cdf - Asymmetric bw | 0.098 | 0.011 | 5300 | 400 | 0.374 |

*Notes:* This table shows the result of density test (Rddensity) on my main sample of analysis, based on Cattaneo et al. (2018), varying the conditional function and the bandwidth.

### D.4.1 Additional Results on Applications

Table E5: Amount of Fees Paid, by Track

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sample | Amount of Fees Paid (All) | Amount of Fees Paid (Track 1) | Amount of Fees Paid (Track 2) | Amount of Fees Paid (Track 3) | Amount of Fees Paid (Track 4) | Amount of Fees Paid (Track 5) |
| Baseline mean (fee-waiver students) | 59.69 | 41.36 | 55.17 | 69.02 | 72.25 | 60.93 |
| Baseline RD estimate | 822*** | 938*** | 759*** | 1039*** | 575*** | 646*** |
| | ( 37) | (108) | ( 90) | ( 90) | ( 92) | ( 59) |
| Robust 95% CI | [748 ; 895] | [725 ; 1150] | [583 ; 934] | [862 ; 1216] | [394 ; 755] | [530 ; 763] |
| Obs. used in estimation | 4,984 | 867 | 920 | 732 | 326 | 521 |
| Total number of obs. | 11,945 | 3,089 | 2,387 | 2,626 | 1,373 | 1,686 |

*Notes:* The table displays the estimated discontinuities in the amount of application fees paid, at the fee waiver threshold, by track. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table F6: Number of Exams Taken, by Track

| Sample | (1) Number of Exams Taken (All) | (2) Number of Exams Taken (Track 1) | (3) Number of Exams Taken (Track 2) | (4) Number of Exams Taken (Track 3) | (5) Number of Exams Taken (Track 4) | (6) Number of Exams Taken (Track 5) |
|---|---|---|---|---|---|---|
| Baseline mean (fee-waiver students) | 22.78 | 24.09 | 24.01 | 28.00 | 23.58 | 10.93 |
| Baseline RD estimate | -12.57*** | -13.46*** | -11.13*** | -15.45*** | -15.88*** | -3.55* |
| | ( 1.27) | ( 3.83) | ( 2.67) | ( 2.83) | ( 3.54) | ( 2.09) |
| Robust 95% CI | [-15.07 ; -10.08] | [-20.98 ; -5.94] | [-16.37 ; -5.89] | [-21.01 ; -9.90] | [-22.81 ; -8.94] | [-7.64 ; 0.54] |
| Obs. used in estimation | 4,709 | 754 | 830 | 827 | 431 | 478 |
| Total number of obs. | 11,945 | 3,089 | 2,387 | 2,626 | 1,373 | 1,686 |

*Notes:* The table displays the estimated discontinuities in the number of exams taken, at the fee waiver threshold, by track. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

### D.4.2 Counterfactual Simulations of the Graduate School Student Matching Algorithm

Table G7: Estimated Percentage Reduction in the Number of Entrance Exams Taken, for Each Cluster of Entrance Exams

| Cluster of Entrance Exams (1) | Percentage Reduction in the Number of Entrance Exams Taken (2) |
|---|---|
| Banque AGRO-VETO BCPST | -28 |
| Banque G2E BCPST | -30 |
| Banque Inter-ENS - BCPST | 0 |
| Banque Mines Ponts PSI | -48 |
| Banque PT | -69 |
| Banque e3a MP | -90 |
| Banque e3a PC | 0 |
| Banque e3a PSI | -90 |
| CCINP MP | -62 |
| CCINP PC | -12 |
| CCINP PSI | -70 |
| CCINP TSI | -55 |
| Centrale-Supélec MP | -42 |
| Centrale-Supélec PC | -90 |
| Centrale-Supélec PSI | -56 |
| Centrale-Supélec TSI | -83 |
| Groupe INSA MP | -63 |
| Mines Ponts MP | -24 |
| Mines Ponts PC | -90 |
| Uncategorized | -82 |
| X - ENS MP | -15 |
| X - ESPCI - ENS PC | -24 |
| X - PSI | 0 |

*Notes:* This table displays the estimated discontinuity in the number of exams taken at the application fee waiver threshold for each cluster of entrance exams. The estimated discontinuities are reported relative to the number of exams taken by individuals below the threshold to represent percentages of reduction. Each cluster corresponds to one cluster for one specific track, with each track having 4 to 5 clusters available.

### D.4.3 Application and Admission to Graduate Schools With Decentralized and Centralized Application Fees

Table H8: Decision to Apply to the Most Selective School, by School Cluster and Track

| | (1) | (2) |
|---|---|---|
| School cluster<br>Application Fees | Cluster 1<br>Decentralized | Cluster 2<br>Centralized |
| Baseline mean<br>(fee-waiver students) | 0.61 | 0.86 |
| Baseline RD estimate | -0.245***<br>(0.077) | -0.072<br>(0.069) |
| Robust 95% CI | [-0.396 ; -0.093] | [-0.207 ; 0.063] |
| Obs. used in estimation | 2,127 | 1,930 |
| Total number of obs. | 8,102 | 8,102 |

*Notes:* The table shows estimated discontinuities in decision to apply to the most selective school of a cluster, around the application fee waiver threshold. Cluster 1 includes elite STEM graduate schools with decentralized application fees for tracks 1, 2 and 3 students; while school Cluster 2 includes elite STEM graduate school with centralized application fees for these students. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table I9: Admission Outcomes to Cluster 1 Schools for Track 1, 2 & 3 Students, by School Selectivity

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Most selective school | Top-tier school | Second-Tier school | Least selective school |
| Years considered | 2015-2020 | | 2019-2020 | |
| Baseline mean (fee-waiver students) | 0.02 | 0.06 | 0.04 | 0.03 |
| Baseline RD estimate | -0.005 | -0.008 | -0.053 | -0.084* |
| | (0.025) | (0.035) | (0.035) | (0.046) |
| Robust 95% CI | [-0.053 ; 0.044] | [-0.077 ; 0.060] | [-0.122 ; 0.016] | [-0.175 ; 0.006] |
| Obs. used in estimation | 1,899 | 2,327 | 840 | 983 |
| Total number of obs. | 8,102 | 8,102 | 3,536 | 3,536 |

*Notes:* The table reports estimated discontinuities in admission outcomes for tracks 1, 2 and 3 applicants, by school selectivity of cluster 1 schools, around the application fee waiver threshold. Cluster 1 schools includes elite STEM graduate school with decentralized application fees for tracks 1, 2 and 3 students. Results concerning the most selective school and top-tier school cover the full period 2015-2020 while results concerning second-tier schools and the least selective school only cover the period 2019-2020 since some of the schools only joined cluster 1 after 2019. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

## E.5 Robustness Tests

Table J10: Admission Probability, Varying Bandwidth Size and Polynomial Order of Estimation

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Receive Admission Offer | Receive Admission Offer | Receive Admission Offer | Receive Admission Offer | Receive Admission Offer |
| Bandwidth | Optimal | Half Optimal | Twice Optimal | Optimal | Optimal |
| Polynomial Order | 1 | 1 | 1 | 2 | 3 |
| Baseline mean (fee-waiver students) | 0.78 | 0.78 | 0.78 | 0.78 | 0.78 |
| Baseline RD estimate | -0.111** | -0.179** | -0.092** | -0.183*** | -0.202*** |
| | (0.054) | (0.086) | (0.045) | (0.069) | (0.078) |
| Robust 95% CI | [-0.216 ; -0.006] | [-0.347 ; -0.010] | [-0.181 ; -0.003] | [-0.319 ; -0.048] | [-0.354 ; -0.050] |
| Obs. used in estimation | 3,623 | 1,875 | 7,077 | 3,723 | 4,458 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 11,945 | 11,945 |

*Notes:* The table shows the estimated discontinuities in probability of admission at the last round of the admission process around the application fee waiver threshold, varying the bandwidth size and polynomial order. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table K11: Admission Probability, Controlling for Track Fixed Effects

| | (1) | (2) | (3) |
|---|---|---|---|
| | Receive Admission Offer (1st round) | Receive Admission Offer (Last round) | Accept Admission Offer |
| Baseline mean (fee-waiver students) | 0.78 | 0.79 | 0.62 |
| Baseline RD estimate | -0.102** (0.050) | -0.107** (0.049) | -0.112** (0.056) |
| Track FE | ✓ | ✓ | ✓ |
| Robust 95% CI | [-0.199 ; -0.004] | [-0.203 ; -0.011] | [-0.221 ; -0.002] |
| Obs. used in estimation | 3,870 | 3,832 | 4,160 |
| Total number of obs. | 11,945 | 11,945 | 11,945 |

*Notes:* The table shows the estimated discontinuities in probability of admission around the application fee waiver threshold, introducing as controls fixed effects for the five different tracks available in prep programs due to some imbalances concerning the distribution of the different tracks below and above the threshold (Table 2). Column 1 shows the probability of being admitted in the first round of the admission process, Column 2 shows the probability of being admitted in the last round, Column 3 shows the probability of accepting an admission offer. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table L12: Probability to Take at Least One Entrance Exam

| | (1) |
|---|---|
| | Take at least one exam |
| Baseline mean (fee-waiver students) | 0.77 |
| Baseline RD estimate | -0.0002 |
| | (0.0003) |
| Robust 95% CI | [-0.0008 ; 0.0005] |
| Obs. used in estimation | 3,221 |
| Total number of obs. | 15,398 |

*Notes:* The table shows the estimated discontinuities in the probability to take at least one high strake entrance exams for the sample of all first year prep program students. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table M13: Admission Probability for Students Observed in First Year of CPGE

| | (1) Receive Admission Offer (1st round) | (2) Receive Admission Offer (Last round) | (3) Accept Admission Offer |
|---|---|---|---|
| Baseline mean (fee-waiver students) | 0.61 | 0.61 | 0.48 |
| Baseline RD estimate | -0.075 | -0.088* | -0.107* |
| | (0.048) | (0.048) | (0.059) |
| Robust 95% CI | [-0.169 ; 0.018] | [-0.182 ; 0.006] | [-0.223 ; 0.009] |
| Obs. used in estimation | 4,553 | 4,319 | 3,952 |
| Total number of obs. | 15,398 | 15,398 | 15,398 |

*Notes:* The table shows the estimated discontinuities in probability of admission around the application fee waiver threshold, among the sample of all prep program students. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table N14: Probability to Take and Gain Admission to Free Exams

| | (1) Take at Least One Free Exam (Any school) | (2) Take at Least One Free Exam (Top school) | (3) Receive Admission Offer From Free Exam School (Any school) | (4) Receive Admission Offer From Free Exam School (Top school) |
|---|---|---|---|---|
| Baseline mean (fee-waiver students) | 0.74 | 0.18 | 0.02 | 0.02 |
| Baseline RD estimate | -0.075 | 0.037 | 0.035** | 0.014 |
| | (0.054) | (0.050) | (0.016) | (0.010) |
| Robust 95% CI | [-0.181 ; 0.031] | [-0.060 ; 0.134] | [0.003 ; 0.066] | [-0.007 ; 0.034] |
| Obs. used in estimation | 4,733 | 3,227 | 4,300 | 3,833 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 11,945 |

*Notes:* The table displays the estimated discontinuities in the probability to apply and be admitted to graduation schools with no application fees for all graduate schools in columns (1) and (3) and for top graduate schools (*Banque X-ENS*) in column (2) and (4). Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

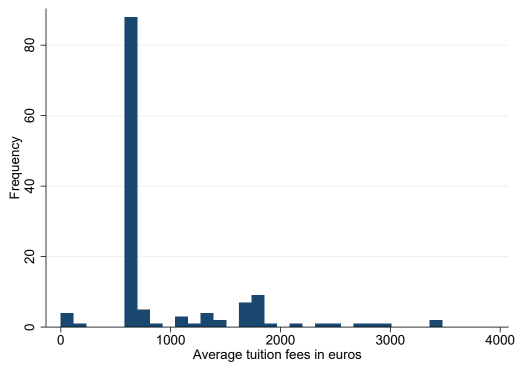
Table O15: Admission Probability, Controlling for the Number of Competitive Exams Taken

| | (1) | (2) | (3) |
|---|---|---|---|
| | Receive Admission Offer (1st round) | Receive Admission Offer (Last round) | Accept Admission Offer |
| Baseline mean (fee-waiver students) | 0.78 | 0.79 | 0.62 |
| Baseline RD estimate | -0.036<br>(0.057) | -0.039<br>(0.055) | -0.047<br>(0.060) |
| Robust 95% CI | [-0.148 ; 0.077] | [-0.146 ; 0.068] | [-0.165 ; 0.071] |
| Obs. used in estimation | 3,551 | 3,736 | 4,284 |
| Total number of obs. | 11,945 | 11,945 | 11,945 |

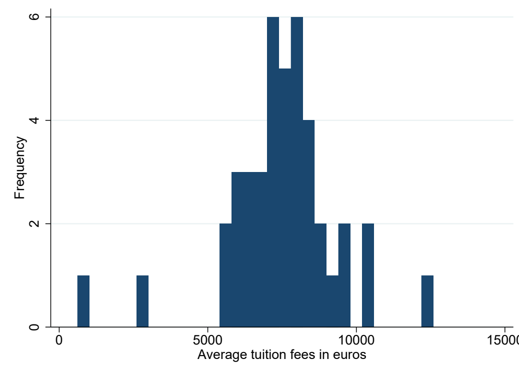
*Notes:* The table shows the estimated discontinuities in probability of admission around the application fee waiver threshold, controlling for the number of exams taken. Column 1 shows the probability of being admitted in the first round of the admission process, Column 2 shows the probability of being admitted in the last round, Column 3 shows the probability of accepting an admission offer. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

## F.6 Tuition Fees

Figure I9: Distribution of Tuition Fees to STEM Public and Private Graduate Schools




(a) Public STEM Graduate Schools




(b) Private STEM Graduate Schools

*Notes:* These histograms depict the distribution of tuition fees to public and private STEM graduate school in France. All amounts are in 2021 constant euros. The amount of tuition fees in STEM graduate school is sourced from CTI (*Comission des Titres d'Ingénieurs*) data.

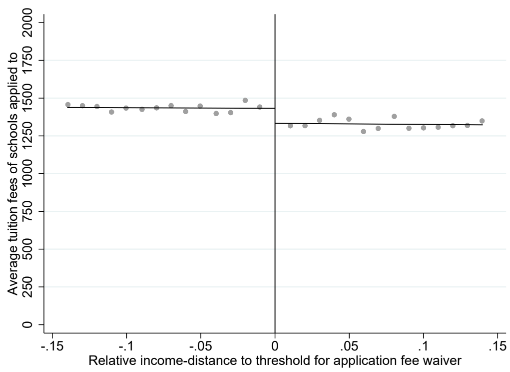
### F.6.1 Robustness Tests: Are Results Driven by Tuition Fee Waiver?

Table P16: Average Amount of Application Fees of Schools Applied To

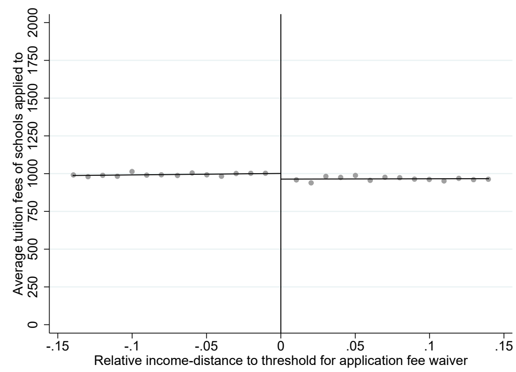
| | (1) Average Amount of Tuition Fees of Application Sent (All Schools) | (2) Average Amount of Tuition Fees of Application Sent (Excluding Private) | (3) Tuition Fees of Grad. School of Admission (All Schools) | (4) Tuition Fees of Grad. School of Admission (Excluding Private) |
|---|---|---|---|---|
| Baseline mean (fee-waiver students) | 1456 | 1001 | 2084 | 30 |
| Baseline RD estimate | -224*** | -35 | -357 | 3 |
| | (63) | (31) | (312) | (45) |
| Robust 95% CI | [-347 ; -100] | [-96 ; 25] | [-968 ; 254] | [-85 ; 91] |
| Obs. used in estimation | 4,237 | 3,313 | 3,740 | 2,217 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 11,945 |

*Notes:* The table shows the estimated discontinuities in the average tuition fees of schools that students choose to apply to. All amounts are in 2021 constant euros. Column (2) and (4) only consider application to public STEM graduate schools, those for which need-based grant applicants are fee exempted. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

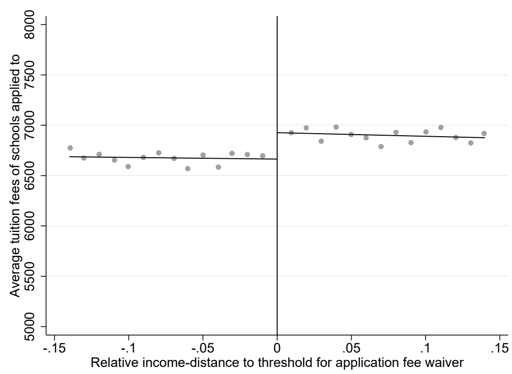
Figure J10: Average Amount of Application Fees of Schools Applied To




(a) All STEM Graduate Schools




(b) Public STEM Graduate Schools




(c) Private STEM Graduate Schools

*Notes:* The circles on the graph depict the average amount of tuition fees of schools that students choose to apply to, as a function of the distance between their parental income and the application fee waiver threshold. Panel a presents this amount for all STEM graduate schools, panel b to public ones and panel c to private ones. The solid lines on the graph represent the estimated values obtained from a first-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver. The amount of tuition fees is sourced from CTI (*Comission des Titres d'Ingénieurs*) data.

Table Q17: Admission Probability, Controlling for Amount of Tuition Fees of Application Sent

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Number of Exams Taken | Number of Exams Taken | Receive an Offer | Receive an Offer |
| Baseline mean (fee-waiver students) | 22.78 | 22.78 | 0.79 | 0.79 |
| Baseline RD estimate | -12.57*** | -10.14*** | -0.11** | -0.10** |
| | (1.27) | (1.17) | (0.05) | (0.05) |
| Average amount of tuition fees of application sent | | ✓ | | ✓ |
| Robust 95% CI | [-15.07 ; -10.08] | [-12.43 ; -7.85] | [-0.21 ; -0.01] | [-0.20 ; -0.00] |
| Obs. used in estimation | 4,709 | 3,658 | 3,760 | 3,626 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 11,945 |

*Notes:* The table shows the estimated discontinuities in the number of exams taken (columns (1) and (2)) and the probability to receive an admission offer (columns (3) and (4)). Columns (2) and (4) control for the average amount of tuition fees of schools where students decide to apply. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table R18: Average Tuition Gain of Applications and Admission

| | (1) Average Tuition Gain of Applications | (2) Average Tuition Gain of Admission School |
|---|---|---|
| Baseline mean (fee-waiver students) | 893.91 | 891.34 |
| Baseline RD estimate | 10.03 | -124.84 |
| | (30.91) | (98.04) |
| Robust 95% CI | [-50.55 ; 70.62] | [-317.01 ; 67.32] |
| Obs. used in estimation | 3,306 | 3,852 |
| Total number of obs. | 11,945 | 11,945 |

*Notes:* The table presents estimated discontinuities in the average tuition gain conferred by need-based grant status for applications submitted and the graduate schools of admission. Tuition gain is calculated as the difference between the sticker price and the amount paid by need-based scholarship students. Typically, the gain is null for private schools and equals the full sticker price for public schools. However, there are exceptions where private schools grant a partial waiver (15%) for need-based scholarship students, or public schools grant a partial waiver (50%) for non-need-based grant students close to the eligibility threshold. All amounts are in 2021 constant euros. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table S19: Number of Applications, by Gain of Tuition Fee

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Applications to Public STEM Schools | Applications to Private STEM Schools | Applications to 1st Quartile of Tuition Gain | Applications to 2nd Quartile of Tuition Gain | Applications to 3rd Quartile of Tuition Gain | Applications to 4th Quartile of Tuition Gain |
| Baseline mean (fee-waiver students) | 65.48 | 6.72 | 6.73 | 15.80 | 25.32 | 24.35 |
| Baseline RD estimate | -16.92*** | -4.24*** | -4.30*** | -4.62*** | -5.30*** | -7.77*** |
| | (2.75) | (0.89) | (0.84) | (0.99) | (1.47) | (0.93) |
| Robust 95% CI | [-22.31 ; -11.52] | [-5.98 ; -2.50] | [-5.94 ; -2.65] | [-6.56 ; -2.69] | [-8.17 ; -2.42] | [-9.59 ; -5.94] |
| Obs. used in estimation | 3,815 | 3,529 | 3,688 | 3,440 | 3,449 | 5,141 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 11,945 | 11,945 | 11,945 |

*Notes:* The table displays estimated discontinuities in the number of applications across different groups of schools. These groups are defined based on the potential tuition fee savings for low-income students. Low-income students benefit from tuition fee waivers only at public STEM schools. The amount of the tuition fee also influences the benefit, with higher sticker price making the waiver more beneficial. The graduate schools are divided into quartiles based on the tuition gain: the 1st quartile consists of schools where the tuition gain is lowest, either because the schools are private or because their fees are relatively low. The 4th quartile includes the most expensive public graduate schools, where the tuition gain is greatest. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

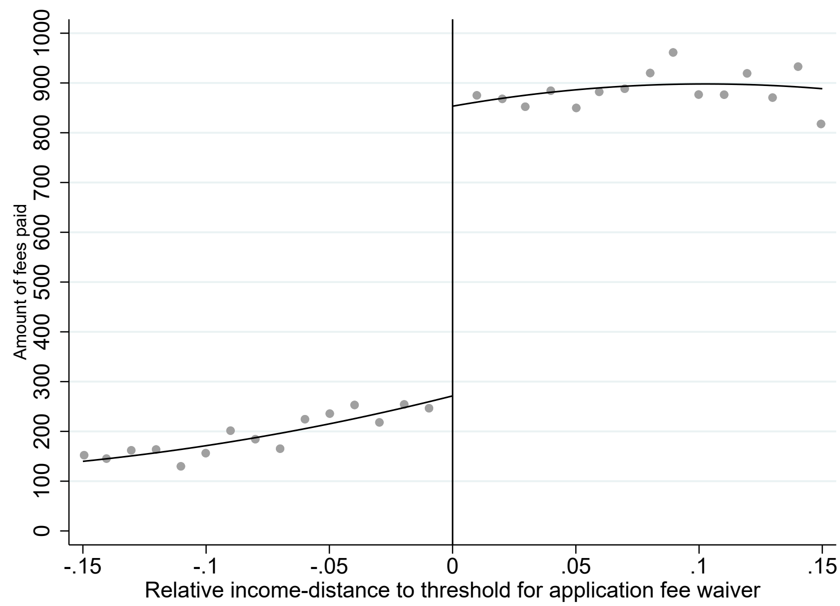
Table T20: Probability of Admission, Excluding Graduate Schools with Tuition Fees Gain

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Admission Proba | Admission Proba | Admission Proba | Admission Proba |
| | (All schools) | (Excluding those with most tuition fee gain) | | |
| | | Q4 | Q3 & Q4 | Q2 & Q3 & Q4 |
| Baseline mean (fee-waiver students) | 0.78 | 0.69 | 0.56 | 0.38 |
| Baseline RD estimate | -0.11** | -0.06 | -0.06 | -0.12 |
| | (0.05) | (0.06) | (0.07) | (0.10) |
| Robust 95% CI | [-0.22 ; -0.01] | [-0.17 ; 0.06] | [-0.21 ; 0.08] | [-0.30 ; 0.07] |
| Obs. used in estimation | 3,623 | 3,293 | 2,323 | 1,113 |
| Total number of obs. | 11,945 | 8,472 | 5,822 | 4,095 |

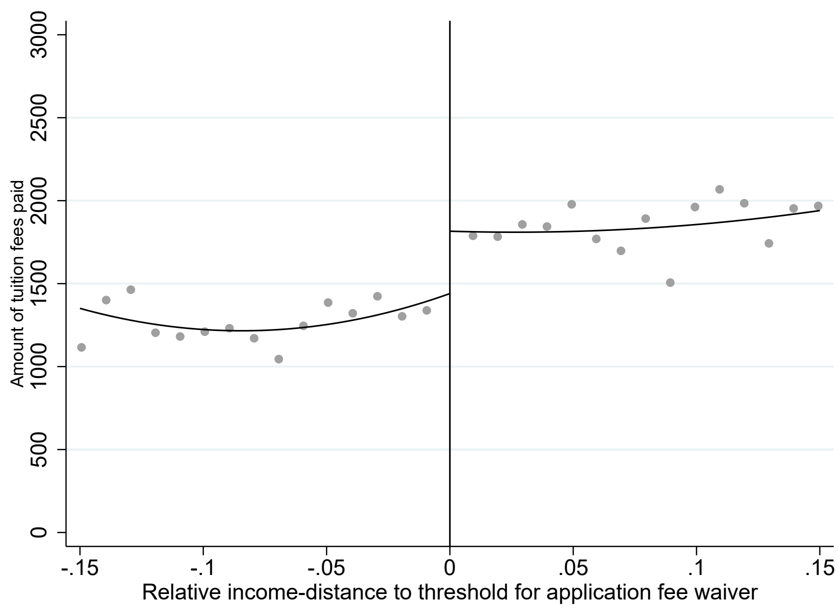
*Notes:* The table illustrates estimated discontinuities in the probability of admission for all graduate schools in column (1), and progressively excluding schools by tuition gain for need-based grants students: schools in the highest quartile of tuition gain are excluded in column (2), those in the third and fourth quartiles in column (3), and those in the second, third, and fourth quartiles in column (4). Graduate schools are divided into quartiles based on the tuition gain. The 1st quartile includes schools where the tuition gain is the lowest, typically because these schools are private or have relatively low fees. The 4th quartile comprises the most expensive public graduate schools, where the tuition gain is the highest. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* × *program* × *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

### F.6.2 Sensitivity to Tuition Fees and Application Fees

Figure K11: Amount of Application Fees and Tuition Fees Paid a the Need Based Grant Threshold




(a) Application Fees




(b) Tuition Fees

*Notes:* The circles on the graph depict the amount of application fees paid (panel a) or tuition fees (panel b) as a function of the distance between applicants' parental income and the application fee waiver threshold. The solid lines on the graph represent the estimated values obtained from a second-order polynomial approximation, estimated separately for both sides of the threshold, based on Calonico et al. (2015). The vertical line marks the eligibility threshold for the application fee waiver. Data on tuition fees are sourced from CTI (*Commission des Titres d'Ingénieurs*). I assume that need-based grant students pay 50 percent of the full price in private STEM graduate schools and nothing in public schools, and I am currently gathering information on this.

Table U21: Admission and Enrollment Probabilities

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Receive Admission Offer (1st round) | Accept Admission Offer | Enrolled in STEM Grad. School | Enrolled in STEM Grad. School Conditionnal on Receiving Offer |
| Baseline mean (fee-waiver students) | 0.78 | 0.62 | 0.62 | 0.75 |
| Baseline RD estimate | -0.113** | -0.118** | -0.154*** | -0.093 |
| | (0.054) | (0.057) | (0.058) | (0.062) |
| Robust 95% CI | [-0.219 ; -0.007] | [-0.229 ; -0.007] | [-0.268 ; -0.040] | [-0.214 ; 0.028] |
| Obs. used in estimation | 3,585 | 4,235 | 3,997 | 2,738 |
| Total number of obs. | 11,945 | 11,945 | 11,945 | 9,320 |

*Notes:* The table shows the estimated discontinuities in probability of admission and enrollment in STEM graduate schools, around the application fee waiver threshold. Column 1 shows the probability of being admitted in the first round of the admission process, Column 2 shows the probability of accepting an admission offer, Column 3 shows the probability to be enrolled in STEM graduate school the next academic year, and Column 4 shows the probability to be enrolled in STEM graduate school the next academic year, while controlling for whether or not the applicant received any admission offer from one STEM graduate school. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table V22: Amount of Application and Tuition Fees Paid

| | (1) | (2) | (3) |
|---|---|---|---|
| | Amount of Application Fees Paid | Theorethical Amount of Tuition Fees Paid | Amount of Tuition Fees Paid |
| Baseline mean (fee-waiver students) | 60 | 2,084 | 1,193 |
| Baseline RD estimate | 823*** | -357 | 575* |
| | ( 37) | (312) | (324) |
| Robust 95% CI | [ 749 ; 896] | [ -968 ; 254] | [ -61 ; 1,211] |
| Obs. used in estimation | 4,984 | 3,740 | 3,702 |
| Total number of obs. | 11,945 | 11,945 | 11,945 |

*Notes:* The table shows the estimated discontinuities in the amount of application fees and tuition fees, around the application fee waiver threshold. Column 1 shows the amount of application fees, Column 2 shows the amount of theoretical tuition fees, i.e. the sticker price of the STEM graduate schools, and Column 3 shows the amount of effective tuition fees paid. Data on application fees paid are directly observed in SCEI administrative data. Data on tuition fees are sourced from CTI (*Commission des Titres d'Ingénieurs*). Information on the amount of tuition fees paid was gathered either directly from graduate school websites or by contacting the graduate schools. Typically, the tuition waiver is null for private schools and equals the full sticker price for public schools. However, there are exceptions where private schools grant a partial waiver (15%) for need-based scholarship students, or public schools grant a partial waiver (50%) for non-need-based grant students close to the eligibility threshold. All amounts are in 2021 constant euros. Each coefficient is the result of a separate nonparametric fuzzy regression discontinuity estimates based on Calonico et al. (2017), where the applicant's relative income-distance to the application fee waiver threshold serves as the running variable. Nonparametric estimates use a triangular kernel, with optimal bandwidths calculated separately for each outcome and sample. Standard errors are shown in parentheses and are clustered at the *track* $\times$ *program* $\times$ *cohort* level. The first panel displays the mean value of the dependent variable for fee waiver applicants. The bottom panel reports 95% robust confidence intervals, observations used in estimation and total number of observations in the sample.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.