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Abstract

The optimal functioning of centralized allocation systems is undermined by the presence of institutions operating off-platform—a feature common to virtually all real-world implementations. These off-platform options generate justified envy, as students may reject their centralized assignment in favor of an outside offer, leaving vacant seats in programs that others would have preferred to their current match. We examine whether sequential assignment procedures can mitigate this inefficiency: they allow students to delay their enrollment decision to potentially receive a better offer later, at the cost of waiting before knowing their final admission outcome. To quantify this trade-off, we estimate a dynamic model of application and acceptance decisions using rich administrative data from the French college admission system, which include rank-ordered lists and waiting decisions. We find that waiting costs are large. Yet, by improving students' assignment outcomes relative to a standard single-round system, the sequential mechanism decreases the share of students who leave the higher education system without a degree by 5.4% and leads to large welfare gains.

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1 Introduction

In countries around the world, college and school admissions are increasingly organized through centralized platforms, motivated by theoretical work highlighting their advantages —particularly in avoiding congestion and justified envy (Roth & Xing, 1997; Abdulkadiroğlu & Sönmez, 2003). Yet, in practice, participants to such centralized platforms typically have access to outside options which undermine their functioning. In the primary and secondary education markets, private and charter schools typically operate outside of the centralized process (Akbarpour et al., 2022). Similarly, in countries running a national college assignment system, such as Chile, Brazil, Germany, and France, a substantial number of higher education institutions remain off-platform. When applicants reject their centralized assignment in favor of an outside offer, they leave vacancies in programs that others would have preferred over their own match, resulting in justified envy (Kapor et al., 2024). Despite its prevalence, this issue remains largely ignored in the design of college and school assignment mechanisms.

In this paper, we empirically investigate whether sequential assignment procedures can mitigate the inefficiencies caused by off-platform options. These mechanisms allow to redistribute offers rejected by students leaving the platform in favor of their outside option, through multiple admission rounds during which students receive a unique offer. They can either accept it or hold it while waiting for potentially more preferred options in subsequent rounds. By allowing students to match with higher-ranked programs, sequential mechanisms may improve match quality and, ultimately, graduation outcomes and welfare. These benefits, however, come at the cost of delayed certainty about final placement: students must wait without knowing whether they will receive a better offer. This uncertainty may generate substantial disutility, as it postpones key decisions, such as securing affordable housing or a student job. Given this dynamic trade-off, whether—and for whom—sequential mechanisms improve educational outcomes, as well as the size and distribution of welfare gains, remains unclear.

The French higher education market provides a unique setting to study this question, as it features a nationwide centralized system with a three-round sequential mechanism that reallocates offers declined by students who opt for off-platform alternatives. We leverage detailed administrative data covering the universe of high school applicants—including their applications, decisions across admission rounds, and enrollment patterns—and combine it with a dynamic model of application and acceptance behavior to quantify the impact of sequential mechanisms on student welfare and graduation outcomes.

We begin by documenting how students respond to the opportunity to delay their acceptance decision across rounds. Among those who do not initially receive an offer from their top-ranked program, only 55% choose to wait in order to be considered for a better offer in a subsequent round. In particular, students from economically disadvantaged households are substantially less likely to delay than those from high socioeconomic backgrounds. At the same time, we document that there can be substantial benefits from delaying, as 29% of the students who do so ultimately receive an offer from a higher-ranked program in a subsequent round. Receiving such an offer is then also associated with a lower probability of dropping out from higher education without a degree. Since delaying their acceptance decision is costless within the platform—applicants retain their initial offer unless they receive a better one—these patterns are consistent with the fact that students incur a disutility from waiting before knowing their final assignment. Sequential mechanisms therefore require students to trade off these waiting costs against the option value of delaying, both of which are likely to be heterogeneous across applicants.

To quantify this trade-off, we build a dynamic model of students' application and acceptance decisions. In the first stage, students submit a rank-ordered list (ROL) of programs to a centralized platform, reflecting their preferences over higher education options. The second stage corresponds to the sequential admission procedure: in each round, students receive at most a single offer and choose whether to accept it, reject it and exit the platform, or hold it and remain eligible for a potentially higher-ranked offer in a subsequent round. This stage captures the dynamic trade-off students face, as the value of delaying incorporates both the cost of waiting—which we allow to be heterogeneous across individuals—and the option value of remaining on the platform, which depends on the likelihood of receiving a better offer and the utility it provides. We allow the utility associated with the offer received to differ compared to the application stage, capturing the fact that students' preferences over programs may evolve throughout their dynamic interactions with the mechanism. We complement this framework with a reduced-form model of graduation outcomes, where the type of tertiary education degree obtained, if any, flexibly depends on the characteristics of the students and the program in which they ultimately enroll.

Rich administrative data from the French sequential admission procedure allow us to identify the primitives of the model. We begin by recovering students' perceived utility of different higher education programs from their submitted rank-ordered list. In a second step, we identify the disutility from waiting, the changes in perceived utility of the programs, the utility associated with the outside option (i.e., exiting the centralized platform), and the probability of receiving a higher-ranked offer, using data on students' offers and acceptance decisions across the three admission rounds. To account for both observed and unobserved heterogeneity, we exploit variation in students' repeated choices—both in their rank-ordered program lists and in their decisions throughout the sequential process. In addition, data tracking student enrollment in both on- and off-platform institutions enable us to identify the parameters governing graduation outcomes. We exploit data on students' location and important measures of socioeconomic status and ability. Furthermore, we allow for individual-level unobserved heterogeneity using a tractable Expectation-Maximization (EM) algorithm, which adapts the Conditional Choice Probability (CCP) approach to our setting (Arcidiacono & Miller, 2011).

Estimated preferences for programs and waiting costs reveal that the latter are substantial: for the median student, the cost of waiting is equivalent to the disutility associated with enrolling in a program located 172 kilometers (107 miles) farther from home. This exceeds the average utility difference between students' second- and first-ranked programs, which corresponds to enrolling 103 kilometers farther away. Overall, waiting costs can deter students from delaying their enrollment decisions: for more than half of them, the utility gain from receiving an offer in a more preferred major would be more than fully offset by the cost of waiting. We also find that waiting costs are substantially higher for students of low socioeconomic status (SES) than for their high-SES peers, indicating that applicants do not benefit equally from the opportunity to access higher-ranked programs offered by sequential mechanisms.

Despite these large waiting costs, counterfactual simulations reveal that the three-round sequential mechanism used in France outperforms a standard one-round alternative, leading to more matches, an increase in college graduation rate, and a substantial increase in welfare for all socioeconomic groups. In particular, the sequential mechanism leads to a three-percentage-point increase in the share of students accepting an on-platform offer. Among students who do not receive an offer from their top-ranked program under the one-round mechanism, 10% receive an offer from one of their higher-ranked programs under the three-round mechanism. Students in vocational and technological high school tracks are the most likely to gain a match through the sequential mechanism, while academic-track students are more likely to enroll in a higher-ranked program than they would under a single-round system. Improved matching outcomes translate into improved graduation outcomes—among students who do not receive an offer from their top-ranked program under the one-round mechanism, the share of students leaving the higher education system without a degree decreases by 5.4%. Ultimately, our welfare analysis shows that students derive a large option value from the sequential mechanism. On average, having the option to delay their decision and wait for better offers, rather than having to make a final decision at the end of a single round, provides a gain equivalent to enrolling 353 kilometers closer to home. Restricting to students who do not receive an offer from their top-ranked program in the first round of the admission mechanism, the mean welfare gain goes up to 861 kilometers.

Related literature. This paper contributes to several strands of the literature. First, it relates to the emerging literature in mechanism design that investigates the consequences of the coexistence of centralized admission platforms and off-platform options. Theoretically, Akbarpour et al. (2022) show that heterogeneity in students' outside options raises equity concerns, with important implications for the choice of mechanism: unlike strategy-proof mechanisms, non-strategy-proof mechanisms benefit students with better outside options, by allowing them to apply more aggressively. Holding the assignment mechanism fixed, Kapor et al. (2024) quantify the welfare costs associated with the existence of off-platform options along with aftermarket frictions created by decentralized waitlists in Chile. They do so through a counterfactual exercise in which additional programs are added to the centralized platform.[1]

While bringing all relevant programs onto the centralized platform can be understood as a first-best solution, it is arguably difficult to implement in practice, as evidenced by the substantial number of off-platform institutions in countries with nationwide centralized admission systems.[2] Students may also consider other types of outside options—such as en-

[1]See also recent work by Bayraktar (2025) who derives conditions under which students without outside options prefer Boston Mechanism to Deferred Acceptance, when other students do have outside options.

[2]In Chile, as of 2023, 22% of the universities did not participate in the centralized admission system, and none of the Professional Institutes were (Larroucau et al., 2025). In Brazil, in 2017, 133 higher education

tering the labor market or studying abroad—which could lead them to exit the platform even if all domestic higher education programs were integrated. In contrast, this paper evaluates an easy-to-implement mechanism design solution—sequential assignment procedures—that explicitly accounts for the dynamic nature of outside options and reallocates rejected offers to students who may prefer them over their initial match, thereby mitigating justified envy.

The properties of sequential mechanisms have been investigated in settings that abstract from the existence of outside options (Luflade, 2019; Klijn et al., 2019; Bó & Hakimov, 2022). We contribute to this literature by identifying a previously unexplored advantage of such mechanisms: their ability to mitigate the inefficiencies that arise when outside options are present. Particularly relevant for our paper is Grenet et al. (2022), as they analyze the timing of offer acceptance in a mechanism with multiple offer rounds. The authors document that students participating in the German university admission system are more likely to accept the first offer they receive, and show that this behavior can be rationalized by a model of learning. At the time of application, students may imperfectly know on-platform programs' quality, and acquiring such information may be costly. In a setting with multiple offer rounds, students are more likely to learn about—and subsequently choose—the program that makes the earliest offer. In this paper, we provide a dynamic model of application and acceptance decisions that allows students' preferences for both inside and outside options to change over time, and we identify an alternative mechanism that plays an important role in accounting for early acceptance behavior: the disutility from waiting before knowing their final assignment. We find that this disutility is substantial and can deter students from taking advantage of the opportunity to receive a higher-ranked offer. Nevertheless, our results indicate that sequential mechanisms remain effective in that they result in substantial improvements of students' graduation outcomes and welfare.

More broadly, and beyond educational settings, this paper contributes to a small but growing literature that models the dynamic considerations induced by allocation mechanisms relying on waitlists—such as those used to assign public housing to households, general practitioners to patients, or deceased donor kidneys to recipients—which involve a trade-

institutions participated in the centralized admission system, out of 2,448 private and public institutions (Machado & Szerman, 2021). In Germany, two centralized clearinghouses that allocate university seats co-habit (one administering programs in medicine-related majors only), but program participation is not mandatory (Grenet et al., 2022). In France, a variety of institutions, from art schools to engineering schools, decided to stay off-platform, for example to preserve the flexibility in their admission calendar and decisions.

off between shorter waiting times and more preferred assignments (Agarwal et al., 2021; Waldinger, 2021; Huitfeldt et al., 2024). We contribute to this literature by quantifying and evaluating the consequences for welfare and graduation outcomes of the dynamic trade-off students face when tertiary education seats are allocated through sequential mechanisms. By comparing the students' welfare under sequential allocation with a counterfactual single round allocation mechanism, our paper also fits into the empirical literature that quantifies the welfare effects of modifications to centralized allocation mechanisms (see, e.g., Agarwal & Somaini, 2018; Calsamiglia et al., 2020; Kapor et al., 2020; Larroucau & Rios, 2022; Combe et al., 2022). The performance of a deferred acceptance algorithm is often found to suffer from the fact that the size of utility differences in the rank-ordered list is ignored. A multi-round version does take it into account as students with the most to gain (net of waiting cost) self-select to participate in future rounds.

Finally, our paper contributes to the large and growing literature studying the determinants of higher education choices, particularly the joint choice of the institution and field of study (see Altonji et al., 2012, 2016, and Patnaik et al., 2021 for reviews).[3] We highlight that the design of the assignment mechanism itself can shape students' major and institution choices in the presence of external constraints—such as waiting costs—which may lead students to forgo options they would otherwise prefer. At a high level, while we do not model decentralized systems directly, this also speaks to the broader trade-off between centralized and decentralized admissions, where simultaneous offers can create bottlenecks. Our results suggest that decentralized systems may disproportionately disadvantage lower-SES students, who face higher waiting costs, and, given the positive correlation between academic achievement and parental income, are also less likely to receive early offers.[4]

The remainder of the paper is organized as follows. Section 2 describes the French higher education system and its sequential centralized college admission procedure, together with the data we use. Section 3 presents descriptive evidence on the dynamic trade-off students face. Section 4 outlines the structural model of student application and acceptance decisions, and

[3]See also recent work by Humphries et al. (2025), who study and estimate a model of college investment decisions in the presence of a centralized college application process.

[4]This concern was raised ahead of France's 2018 shift from the centralized APB system to the more decentralized Parcoursup (Villani & Longuet, 2018). See also 'Parcoursup : la recherche d'un logement ou l'autre galère des étudiants "en attente"', Marianne, Anthony Cortes (published on August 22^{nd}, 2018, last accessed: May 28^{th}, 2025) and 'Quand Parcoursup complique la recherche d'un logement social', Libération, Timothée de Rauglaudre (published on May 29^{th}, 2018, last accessed: May 28^{th}, 2025). This paper provides a framework allowing to capture some of these considerations.

Section 5 details the identification and estimation strategy. Section 6 presents the estimation results and Section 7 describes the counterfactual exercises we perform. Finally, Section 8 concludes.

2 Institutional Context and Data

This section first provides an overview of the French higher education market before detailing the centralized college admission procedure. It then describes the data sources used throughout the paper. We focus on 2015, during which a mechanism based on a sequential deferred acceptance algorithm, Admission Post-Bac (APB), was in place.[5]

2.1 The French Semi-Centralized Higher Education Market

Higher education in France is regulated by the Ministry of Education. Students are eligible to enroll in a post-secondary program conditional on obtaining a passing grade at the national end-of-high school exam.[6] The content of this exam is determined by students' choice of track (*academic*, *technological* or *vocational*) and high school major.[7]

As in many countries such as Chile, Brazil, and Germany, the application and admission procedures in France can be described as semi-centralized. Most programs participate in a centralized admission platform operated by the Ministry of Higher Education, where an algorithm assigns students to programs based on their rank-ordered application lists and the programs' priority rules, as we describe below. Yet, a non-negligible share of the higher education institutions operate off-platform, by collecting applications and making admission decisions in a decentralized manner. The choice of operating off-platform allows programs to retain complete autonomy on their admission procedure, and can often be explained by historical reasons. In France, off-platform programs represent 13% of the first-year higher education programs available and enroll about 12% of the students in their first year of post-secondary education. See Appendix A.2 for details on the off-platform programs.

[5] APB was replaced by Parcoursup in 2018. Although it still shares some of its sequential features, it is less standard as it does not ask for rank-ordered lists of students.

[6] Appendix A provides more details regarding the high school system in France.

[7] In the empirical analysis, we will distinguish between four track-major bundles, by distinguishing students in the academic high school track according to whether they major in sciences or in humanities and social sciences.

Table A-1 shows that the characteristics of on- and off-platform programs overlap: public (typically free) and private programs can be found both in- and off-platform, and so are different majors, such as STEM, Economics/Law/Business, or Humanities. As a consequence, many high school graduates wishing to enter higher education are likely to both participate in the centralized procedure and submit applications off-platform. The presence of such off-platform options has important implications for the outcome of the centralized admission system: receiving an offer from an off-platform program can induce students to decline the assignment received on-platform, thereby freeing up a seat that could be allocated to another student.[8] This makes it key to design a centralized procedure allowing to dynamically redistribute seats left vacant by students enrolling off-platform.

2.2 A Centralized Procedure with Multiple Rounds

The centralized admission procedure operates on an online platform, 'Admission-Post Bac' (APB), gathering about 87% of the first-year higher education programs. Students in their final high school year register on this platform and are asked to submit a rank-ordered list of up to 36 programs (with a maximum of twelve per *type* of program). The five *types* of programs—Bachelor programs, prep-school programs, technical programs, vocational programs, and other programs offered by engineering and business schools—are described in Table A-1.[9] Given the students' rank-ordered lists and the priorities set by each program, matches are determined by the clearinghouse using a college-proposing deferred acceptance (DA) algorithm.

The nature of priorities used to rank applicants depends on a program's type. On the one hand, prep-school programs, technical programs, vocational programs, and programs offered by business and engineering schools typically do not disclose the criteria they use to determine priority, and are simply known to consider academic performance as a criterion.

[8] Importantly, off-platform institutions do not coordinate on the timing of their offers, implying that students may receive their centralized assignment while still waiting to know about their outside options.

[9] Bachelor programs are three-year university programs at the end of which students obtain a Bachelor's degree. Prep-schools programs are highly selective two- to three-year programs that prepare students to take competitive exams for admission to the most prestigious public and private engineering schools, business schools, and other higher education institutions in France. Technical programs are two-year technology-oriented programs, tailored to train mid-level technical professionals. Vocational programs typically place a stronger emphasis on internships and also last two years. Finally, a number of (less prestigious) engineering and business schools offer three- to five-year programs in which students can enroll right after high school, without the need to go through a prep-schools program.

On the other hand, by law, Bachelor's programs are not allowed to give admission priority based on academic performance. Instead, these programs typically rank applicants using coarse priority groups based on the applicant's residential location (whether the applicant lives in the region where the program is located) and the absolute rank of the program in the applicant's ROL.[10] A random lottery number is then used to rank applicants within priority groups.

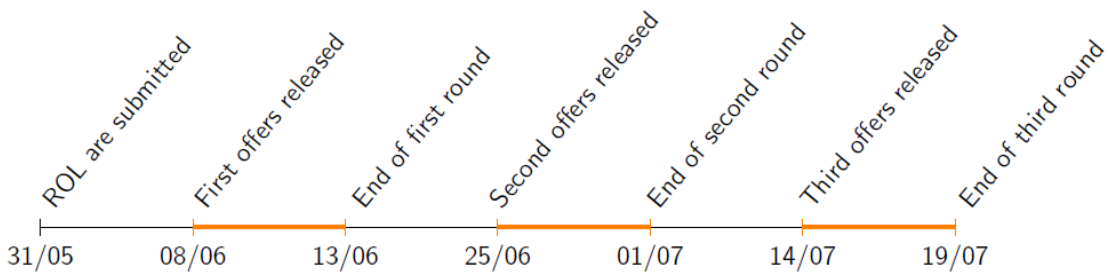
Applicants in 2015 had little to no information about their priority to different programs. First, from the perspective of students, no priority score was ever disclosed, neither at the time of application, nor at any point during or after the process. Past admissions cutoffs, which are available to applicants in many other settings studied in the literature, were never made public in this context. Second, the criteria themselves used to determine priorities to Bachelor programs were unknown to the public. The use of lottery numbers and the role of their own ROL in the determination of their priority were unknown to the students. The latter is particularly important, as it could give rise to strategic incentives in forming the rank-ordered list. However, it is important to note that this concern only rose after the court-order publication of the algorithm source code in October 2016. Until then, students were only aware of the role of residential location in determining priority (Grenet, 2022). Importantly, the only guideline provided to students was to report their preferences truthfully in their ROL.

A key feature of this centralized admission platform is that it is designed to introduce some flexibility to students' acceptance decisions, through the use of a multi-round assignment mechanism. In particular, while the deferred acceptance algorithm generates a unique assignment for each student, it is run several times in order to redistribute seats left vacant by students who applied to the centralized platform but eventually declined the offer they receive from the platform. Specifically, after receiving a first assignment from the platform, students can choose among three options. They can (i) *accept* the assignment immediately and proceed with enrollment; (ii) *drop out* of the platform by declining the offer, thereby returning the seat to the vacancy pool; or (iii) *delay* their decision and participate in the next round, i.e. holding on to their assignment while maintaining applications to programs

[10] Figure A-1 shows the map of academic regions (*académies*) used for the determination of priority. Note that priorities also take into account whether the applicant is entering higher education for the first time: we restrict our analysis to such students, switchers representing only 12.38% of the applicants on the platform.

ranked higher than the current offer in their ROL.[11] The matching algorithm is then rerun to assign the remaining vacancies to unmatched students and those who chose to delay their decision, using the same ROLs and priorities as in the first round, but excluding students who have either accepted an offer or exited the platform. After receiving their second-round offer, students may again *accept*, *drop out*, or *delay*. In the third and final round, the clearinghouse produces a final set of offers, which students can only accept, or refuse and drop out. Figure 1 illustrates the timing of the process, as implemented in 2015.

Figure 1: Multiple assignment rounds timeline in 2015



NOTES. This figure shows the timeline of the assignment procedure for 2015. In rounds one and two, students submit their decision to accept, drop out, or delay between the release of the offers and the end of the round.

2.3 Data

The empirical analysis of this paper combines two administrative datasets from the French Ministry of Higher Education (Research and Innovation department, SIES). First, we use detailed administrative data from the centralized college admission platform. This dataset gathers information on the universe of applicants each year, including demographic characteristics, their residential ZIP code, the high school they are enrolled in, the track and major chosen in high school, and high school grades (which we use to construct a Grade Point Average, GPA). It also shows the characteristics of all on-platform programs, including their type, major, and location.[12] Finally, it provides detailed information on all activities within

[11]Note that students assigned to their top-ranked choice cannot *delay* as there is no program ranked higher than their current offer in their ROL. In practice, there is also a fourth option in which students reject the offer and still participate in the next round. As this is difficult to rationalize and only a negligible number of students used this option, we exclude it from the analysis.

[12]We supplement these data with publicly available information about the cost of housing in France's major cities. Details are provided in Appendix A.2.

the platform: the rank-ordered list submitted by each applicant, their assignment offer in each round (if any), and their decisions (accept, drop out, or delay) for that round.

We focus on the 2015 assignment procedure.[13] Table A-2 describes applicants' characteristics as well as their final assignment. Students submit on average slightly less than seven applications, far from the maximum number of applications allowed. Their final assignment is on average ranked strictly higher in their rank-ordered list than the first offer they receive, illustrating the redistribution of seats through the sequential assignment procedure. We return to this feature below as we explore the benefits of choosing the option to *delay*.

The second administrative dataset (SISE, *Système d'Information sur le Suivi de l'Etudiant*) we use tracks students enrolled in the French higher education system. It includes the vast majority of institutions — whether on- or off-platform — with some exceptions, such as nursing schools. For each academic year, the dataset describes the program (major and institution) in which the student is enrolled, and the diploma obtained, if any. This information allows us to construct graduation outcomes for the applicants observed in the dataset described above.

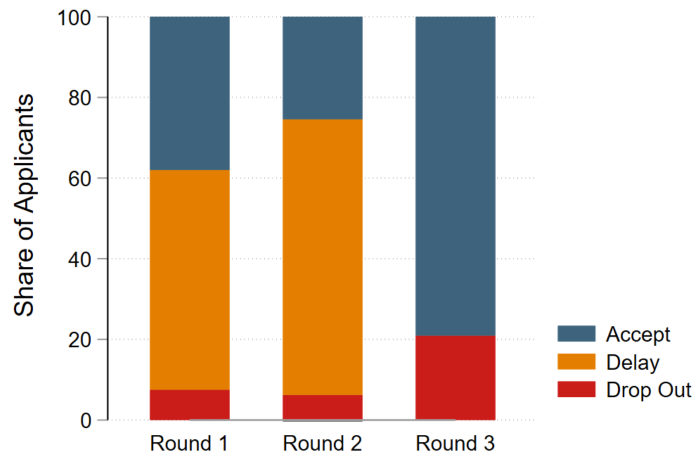
3 Descriptive Analysis of the Option to Delay

This section documents students' behavior across the three admission rounds, focusing on their use of the option to delay. We show that there are clear gains from delaying, as a substantial fraction of students who *delay* eventually receive a higher-ranked offer in a subsequent round. Yet, we also document that there is significant heterogeneity in the probability to choose *delay*, in particular across SES groups, suggesting heterogeneity in the costs of waiting for one's final assignment. We summarize these patterns by highlighting four key facts.

Fact 1: Not all students choose to *delay*. We first document that a significant share of students do not take advantage of the opportunity to receive an offer from a higher-ranked option in a subsequent round. Figure 2 illustrates the extent to which students choose to delay their decision. Focusing on students who did not receive an offer from their top-ranked

[13] We restrict attention to students who completed high school in mainland France, that is, excluding those enrolled abroad or in French overseas regions—and who were in their final year of high school at the time of application. We also exclude students who fail at the final high school exam (*Baccalauréat*), representing 6.34% of the applicants.

Figure 2: Decision Shares by Admission Round



NOTES. This figure shows the share of students who accept, delay, and drop out in each round, conditional on *not* having received an offer from their top-ranked choice.

choice (and are therefore eligible to use the delay option), it shows the share choosing to accept, delay, and drop out in each assignment round. In the first round, about 55% of these students decide to delay their decision, while slightly less than 40% decide not to wait for a better option and accept their offer. In the second round, almost 65% of the participants choose to delay, while about 25% do not wait and accept their assignment. In the third round, when students cannot choose to delay, 85% of the participants accept their assignment while the rest drop out.

If there are benefits from delaying, such patterns are consistent with the fact that it may be costly for students to wait before receiving their final assignment. We next explore the benefits associated with delaying, before turning to potential drivers of waiting costs.

Fact 2: *Delaying* is associated with substantial benefits. Table 1 illustrates the expected benefits of choosing the delay option. 18% of students choosing to delay in round 1 receive a new (higher-ranked) offer in the second round. This offer is, on average, ranked 2.48 ranks above the offer they received in round 1. In round 3, 19% of the students delaying in rounds 1 and 2 receive a better offer compared to round 2.[14] The latter is ranked on average 2.73 ranks above the offer they hold on to at the end of round 2. These are large improvements, considering that applicants list on average 6.6 programs only.

[14]Overall, 29% of the students who delay in the first round receive an offer from a higher-ranked program in a subsequent round.

Table 1: Assignment Improvement from Delaying

	Share Receiving Better Offer	Mean Rank Improvement
Round 2 vs Round 1	0.18	2.48
Round 3 vs Round 2	0.19	2.72
Overall	0.29	2.59

Notes. This table reports the share of students receiving a higher-ranked offer, conditional on receiving an offer in the first round and delaying. The first two rows consider an offer in the current round, conditional on delaying in the previous round. The last row considers the improvement of the final offer for students that delayed at least once.

In Table 2, we provide evidence that receiving a higher-ranked offer after choosing to delay is associated with a significantly higher probability to enroll in any higher-education program, and a lower probability to leave the higher education system without a degree. Specifically, we consider the following regression:

$$Y_i = \beta_0 + \beta_1 D_i + \mathbf{X}_i' \beta_2 + \epsilon_i \tag{1}$$

where D_i is an indicator variable equal to 1 if student i received an offer at round 2 or 3 that is different from (and therefore higher-ranked than) the round-1 offer, and 0 otherwise; and $\mathbf{X}_i$ is a vector of individual characteristics, including high school GPA.

Columns (1) and (2) of Panel A show estimates obtained for β_1 when estimating Equation (1) using an indicator of whether i enrolled in any higher education program (not only on-, but also off-platform) in 2015 as outcome Y_i, and restricting the sample to students who received a first round offer *and* choose to delay in the first round. We find that those who receive a later-round offer are 3.6 percentage points more likely to enroll in the higher education system than the average student who delays in the first round. Columns (3) and (4) present estimates from the same equation, using as outcome Y_i an indicator of whether i exits the higher education data without ever being recorded as earning a degree by the end of the academic year 2022-23. Estimates show that those who receive a later-round offer are 3.4 percentage points less likely to leave the higher education system without a degree than the average student who delays in the first round. The negative association between leaving the higher education system without a degree and receiving a higher-ranked offer after using delay is robust to restricting the sample to those who do enroll in some higher education program in 2015 (Columns (5) and (6)).

While this analysis is not causal, it indicates that allowing students to be matched to a higher-ranked program is associated with significantly better educational outcomes. This is also consistent, in particular, with recent results from the literature that leverage the random lottery number assigned to APB applicants to over-subscribed Bachelor programs (Bechichi & Thebault, 2021).

Table 2: Impact of Receiving an Improved Offer on Enrollment & Graduation

	Enroll		Do Not Graduate			
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Students Delaying in Round 1						
Better Offer Received	0.033	0.036	-0.031	-0.034	-0.019	-0.028
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Baseline	80.88	80.88	29.53	29.53	20.20	20.20
Controls	No	Yes	No	Yes	No	Yes
Obs.	76,930	76,930	76,930	76,930	62,223	62,223
Panel B: Students Without Offer in Round 1						
Received Later-Round Offer	0.286	0.236	-0.193	-0.117	-0.111	-0.055
	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)	(0.007)
Baseline	34.56	34.56	73.45	73.45	46.77	46.77
Controls	No	Yes	No	Yes	No	Yes
Obs.	58,526	58,526	58,526	58,526	20,224	20,224

Notes. This table shows the estimates from β_1 from estimating Eq. (1). Panel A restricts attention to the sample of students who receive a first round offer *and* choose to delay in the first round (Columns (1) to (4)). In Columns (5) and (6), the sample is further restricted to students who are enrolled in some higher education programs in 2015. Panel B focuses on the sample of students without offer in the first round (Columns (1) to (4)). In Columns (5) and (6), the sample is further restricted to students who are enrolled in some higher education programs in 2015. Columns (2), (4), and (6) includes controls for the student's high school track, high school GPA and, for Panel A, the rank of the offer received in round one.

Fact 3: The benefits of the multi-round procedure extend to those who do not receive an offer in the first round. Almost 14% of all applicants do not receive any offer in the first round. The sequential mechanism used in France allows for the redistribution of rejected seats to unmatched students: a substantial share (25%) of those students end up receiving an offer in a later round.

We estimate Equation (1) for the sample of applicants who do not receive an offer in the first round. Panel B of Table 2 shows that those who receive a later-round offer are 24 percentage points more likely to enroll in the higher education system (Column (2)) and 12 percentage points less likely to exit the higher education system without a degree (Column (4)) compared to the average student who did not receive an offer in the first round. This large

Table 3: Share of Eligible Students Choosing to *Delay*, by SES

	Round 1	Round 2
High SES	0.57	0.71
Medium-High SES	0.55	0.68
Medium-Low SES	0.54	0.66
Low SES	0.50	0.63

NOTES. This table shows the share of students who choose to delay in each round, conditional on *not* having received an offer from their top-ranked choice, by SES.

and negative association between leaving the higher education system without a degree and receiving a later-round offer is robust to restricting the sample to those without a first-round offer who do enroll in some higher education program in 2015 (Column (6)).

Fact 4: Heterogeneity in the use of *delay*. We document heterogeneity in the use of delay along individual and offer characteristics. Table 3 reports the share of students choosing the delay option in each round (among those who did not receive an offer from their top-ranked choice) broken down by SES.[15] The table shows the existence of a gradient across SES in the use of the delay option. In particular, high-SES participants are seven (eight) percentage points more likely to choose *delay* than low-SES participants in round 1 (round 2). This heterogeneity is consistent with low-SES students facing more financial pressure than their high-SES counterparts, which may result, in turn, in a greater disutility of waiting before securing housing or a student job.

We also find suggestive evidence that students' likelihood of delaying their acceptance decision depends on the geographic location of both current and potential future offers. In particular, students holding an offer from a program in their home region are less likely to delay in the second round when their top-ranked program is located outside their region (Table A-4). This pattern is consistent with students anticipating that receiving an out-of-region assignment late in the summer could make it difficult to secure affordable accommodation.

Additionally, we find that students are significantly more likely to delay when holding an offer from a lower-ranked program, so that there is a larger set of programs from which they may get an offer from in the next rounds (Table A-3). This suggests that students take into account the option value associated with delaying when making their decision.

[15] See Appendix A.1 for a definition of the different SES categories.

In the next section, we develop a structural model that builds on these descriptive patterns and allows us to analyze how students trade off the disutility of waiting with the option value associated with delaying.

4 A Dynamic Model of Student Behavior in Sequential Admission Mechanisms

We build a structural model of student behavior in a sequential admission mechanism, as implemented in France with the APB system. The model captures the two-stage decision process that students undergo on the platform. In the first stage, students submit a rank-ordered list of programs, reflecting their preferences over higher education options. The second stage corresponds to the sequential admission procedure and is therefore dynamic: in each round, students receive, at most, a single offer and choose whether to accept it, reject it and exit the platform, or hold on to it and remain eligible for a potentially higher-ranked offer in a subsequent round. We complement this framework with a reduced-form model of graduation outcomes, where the type of tertiary education degree obtained, if any, depends flexibly on students' characteristics and on the offer they ultimately accept on the platform, should they accept one.

4.1 Stage 1: Rank-Ordered List Submission

When students log into the online platform, they are asked to submit a rank-ordered list of programs to which they wish to apply. We assume that students report their preferences truthfully, as explicitly recommended by the platform. We return to this after introducing students' first-stage payoff.

Utility over programs. We assume that students rank programs according to the perceived utility of being matched to them, denoted by u_{ij} for program $j \in \mathcal{J}$, where $\mathcal{J}$ is the set of programs available on the platform, and a random shock η_{ij}:

$$u_{ij} + \eta_{ij} = u_j(S_i, \tau_i, d_{ij}) + \eta_{ij}. \tag{2}$$

The utility u_{ij} is a j-specific function of a vector of observed student characteristics S_i, an unobserved (but known by the student) heterogeneity type τ_i, and the distance between the student residence and the program location, d_{ij}. It captures the perceived lifetime utility of enrolling in program j at the time of application, reflecting both its expected consumption value while enrolled in the program and its implications for longer-term outcomes, such as graduation and job prospects. We assume a discrete distribution of unobserved heterogeneity types with finite support. η_{ij} captures the unobserved shock associated with applying to program j, which we assume to be identically and independently distributed across students i and programs j according to an Extreme Value Type 1 distribution with scale parameter σ.

Ranking Behavior. On the platform, we assume that student i submits a ROL, denoted by $\mathcal{R}_i$, by truthfully ranking programs according to $u_{ij} + \eta_{ij}$.[16] This implies that the program ranked r^{th} by student i, denoted d_{ir}^{ROL}, yields the highest utility among the set of programs that are not already ranked above position r, that is:

$$d_{ir}^{ROL} = \underset{j \in \mathcal{J} \setminus \{d_{ik}^{ROL}\}_{k=1}^{r-1}}{\arg\max} \; u_{ij} + \eta_{ij}$$

Remark. As described in Section 2, no information was disclosed to the public regarding students' priority score to different programs, nor the existence of strategic incentives stemming from the fact that the applicant's priority for a Bachelor program is a function of the program's rank in their ROL. Importantly, the only guideline available to applicants was to rank programs in preference order. As a consequence, it seems reasonable to assume that students truthfully report their preferences in their ROL.

Besides, this assumption is made more plausible by the fact that the number of applications that can be submitted on the online platform is relatively large: students can rank up to 36 programs, which is substantially more than in several other centralized systems that have been studied in the empirical school assignment literature, such as in Chile (10 programs) or Germany (12 programs). We observe that fewer than 1% of the applicants submit 36 choices, with students submitting an average of 6.61 applications (Table A-2). Also consistent with

[16] As reflected in the likelihood Equation (7), our empirical strategy does not require strict truth-telling and accommodates truncation strategies. Our assumption is that (i) alternatives are ranked in decreasing order of preference, and (ii) ranked alternatives are preferred to non-ranked alternatives. We do not assume that the outside option is preferred to non-ranked alternatives.

students being truth-telling, among students submitting at least two applications, there is virtually no decline in the share ranking a selective Bachelor program (in Law, Psychology or Sports Science) at rank 1 (10.9%) and at rank 2 (10.8%).

Finally, this assumption is further supported by the argument that truth-telling—or a simple strategy close to it, such as truncation—may be the best course of action for participants with limited information about the mechanism or others' preferences, even when the mechanism is not strategy-proof. In particular, Fack et al. (2019) show that truth-telling is more likely to be satisfied when students can rank many programs and face large uncertainty about each program's exact ranking of students, as in the French context. Roth & Rothblum (1999) also emphasize that, even in the relatively simple case of the school-proposing Deferred Acceptance (DA) algorithm, identifying profitable deviations from truthful reporting requires students to possess information they typically lack. In particular, a given manipulation may be beneficial under some configurations of priorities and preference profiles, but may lead to strictly worse outcomes under others. Successfully identifying profitable strategies therefore requires reliable knowledge about priorities and preferences of others, information to which students in our setting arguably do not have access. Related, recent work by Troyan & Morrill (2020) formalize the idea of obviously profitable manipulations—i.e., deviations that dominate truth-telling based solely on knowledge of the best- and worst-case outcomes of each action. They conclude that the school-proposing DA is not obviously manipulable.

4.2 Stage 2: Dynamic Model of Student Enrollment Decisions

The second stage of the model corresponds to the admission phase of the sequential mechanism, which captures students' decisions in the three rounds of the procedure. At the beginning of each round $t \in \{1, 2, 3\}$, each student receives a unique offer $j_t \in \mathcal{J} \cup \{0\}$, where $j_t = 0$ if the student does not hold any offer in round t.

If $j_t \neq 0$ and $t < 3$, students can choose between three actions $k \in \{1, 2, 3\}$: accept the offer ($k = 1$), delay the decision and remain eligible for future rounds ($k = 2$), or drop out from the platform ($k = 3$). In the final round ($t = 3$), only two options are available: accept ($k = 1$) or drop out ($k = 3$). If no offer is received in round t (i.e., $j_t = 0$), students may either wait for the next round ($k = 2$) or exit the platform ($k = 3$).

Within a given round, we assume that students choose the available option that maximizes their expected lifetime utility, denoted $v_{ikt} + \epsilon_{ikt}$, with v_{ikt} the conditional value function associated with choice k and ϵ_{ikt} an idiosyncratic preference shock, independently drawn from a mean-zero extreme value type 1 distribution, which is revealed to students in round t.[17] As is common in dynamic matching models, we assume that shocks (here, ϵ_{ikt} and η_{ij}) are independent over time (Agarwal et al., 2021). However, as in, e.g., Arcidiacono (2005), we do allow for correlation of unobserved preferences across all stages and periods through the introduction of an unobserved heterogeneity type. We now discuss the conditional value functions associated with each option.

Accept ($k = 1$). The conditional value function associated with accepting the offer received in round t is defined as follows:

$$v_{i1t} = u_{j_t}(S_i, \tau_i, d_{ij_t}) + w_{j_t}(S_i, \tau_i), \tag{3}$$

where $u_{j_t}(S_i, \tau_i, d_{ij_t})$ corresponds to the utility of being admitted to program j_t, as defined above, and $w_{j_t}(S_i, \tau_i)$ captures the fact that the perceived utility derived from accepting a program in round t may differ from the perceived utility at the time of submission of the ROL. The latter component accommodates the possibility that students learn about their preferences over time. This specification also nests a model in which the value of certain program characteristics changes over time—for instance, location, possibly reflecting tensions on the housing market which may vary over the course of the admission procedure.[18]

Delay ($k = 2$). Students can alternatively decide to wait for better options while not losing the currently assigned alternative. In this case, they incur a waiting cost in the current period: $\omega_i = \omega(S_i, \tau_i)$. This cost is assumed not to depend directly on the characteristics of the student's offer or listed programs. This cost of waiting can be monetary, but it can also reflect psychic costs. One would expect an impatient student to have high (psychic) waiting costs; a student who tends to procrastinate would have low (or even negative) such costs (Akerlof, 1991). Importantly, in addition to waiting costs, the value of delaying also depends on the continuation value that captures their (weakly) improved offer in the next

[17] See also, among others, Abbring & Daljord (2020) who set the mean of the preference shocks to zero instead of the Euler constant.

[18] We normalize $w_{j_t}(S_i, \tau_i)$ such that, for all S_i and τ_i, there exists an option j for which $w_j(S_i, \tau_i) = 0$. Differences across students in the propensity to accept any offer, regardless of its characteristics, will thus be captured by the utility of dropping out from the platform, which we define below.

round, yielding the conditional value function:

$$v_{i2t} = -\omega_i + \sum_{j' \in \mathcal{R}_i^{j_t} \cup \{j_t\}} \Pr(j_{t+1} = j' | \Omega_{it}) \bar{V}_{it+1}(\Omega_{it}, j_{t+1}) \tag{4}$$

where $\Pr(j_{t+1} = j'|\Omega_{it})$ denotes the probability to receive an offer from program j' in the next round, $t+1$, conditional on their information set Ω_{it}. $\mathcal{R}_i^{j_t}$ denotes the set of options in $\mathcal{R}_i$ that are ranked above j_t, while $\bar{V}_{it+1}(\Omega_{it}, j_{t+1})$ denotes the expected value of behaving optimally in the next round, conditional on the current information and the offer received, j_{t+1}. We hereby assume that students keep track of their time-invariant individual characteristics S_i, heterogeneity type τ_i, ROL $\mathcal{R}_i$ and the time-varying round t and offer j_t, that is, $\Omega_{it} = (S_i, \tau_i, \mathcal{R}_i, t, j_t)$.

Drop out ($k = 3$). Finally, students can decide to drop out from the platform, which is associated with the outside option utility:

$$v_{i3t} = u_{0t}(S_i, \tau_i). \tag{5}$$

This term allows for heterogeneity in students' outside options depending on their characteristics S_i and heterogeneity type τ_i. This accommodates, in particular, differential value of (or access to) off-platform options along these dimensions. The outside option utility is also indexed by round t to capture the possibility that outside options may evolve over the course of the centralized admission process, as different off-platform programs release their offers at different dates.[19]

4.3 Graduation

We complement the above framework with a reduced-form model of graduation outcomes. Let d_i denote student i's higher education graduation outcome, which can take one of $M + 1$ distinct values. Specifically, $d_i = m \in \{1, 2, \dots, M\}$ corresponds to earning a higher education degree of type m, characterized by a program type–major pair that is offered on- or off-platform, while $d_i = 0$ indicates that the student exits the higher education system.

[19] We provide in Section 5.2 the parameterization we use for the outside option utility, which is assumed to be additively separable in its time-varying and individual-specific components.

We assume that graduation d_i is given by the following unordered choice model:

$$d_i = m \in \{0, 1, \dots, M\} \text{ iff } h_m(S_i, \tau_i, j_i) + e_{im} > h_{m'}(S_i, \tau_i, j_i) + e_{im'} \;\; \forall m' \neq m. \qquad (6)$$

We denote by j_i the on-platform program student i enrolls in, with the convention that $j_i = 0$ if student i does not enroll in an on-platform program. Consistent with the idea that part of the perceived utility from enrolling in a given program j_i may reflect expected graduation outcomes, we allow the graduation index, $h_m(S_i, \tau_i, j_i)$, to depend on the same student characteristics as the utility function u_{ij_i}, along with the characteristics of the matched program j_i. In particular, $h_m(S_i, \tau_i, j_i)$ depends flexibly on student i's unobserved type and observed characteristics, including high school GPA and track; and whether student i got matched with a program by the assignment mechanism and enrolled in this program (i.e., $j_i \neq 0$). If so, h_m also depends on the major and type of the student's assigned program j_i, and the rank of j_i in student i's ROL. Finally, the $(e_{im})_m$ are i.i.d Type 1 Extreme Value distributed shocks.[20]

5 Identification and Estimation

We begin by discussing the identification and parameterization of the model. Then, to facilitate exposition, we present the estimation approach under the assumption that the student type τ_i is observed, describe how the model can be estimated without solving the dynamic program (using a Conditional Choice Probability, or CCP, approach), and finally explain how we allow τ_i to be unobserved by the econometrician.

5.1 Identification

For the sake of exposition, we first consider the case without type-specific unobserved heterogeneity (i.e., τ_i observed to the econometrician), before briefly discussing the identification of the unobserved heterogeneity parameters.

Utility over programs. As students are assumed to be truthful when ranking higher education options, we identify their preferences over the on-platform programs — up to

[20]The exact parameterization of the model is shown in Equation (B-2) in Appendix B.

scale — directly from the observed submitted ROLs. In particular, given the specification discussed in Section 4.1, the likelihood of observing the ROL of student i is given by the well-known rank-ordered (or exploded) logit probabilities:

$$\frac{\exp(u_{id_{i1}^{ROL}}/\sigma)}{\sum_{j\in\mathcal{J}}\exp(u_{ij}/\sigma)}\times\frac{\exp(u_{id_{i2}^{ROL}}/\sigma)}{\sum_{j\in\mathcal{J}\setminus\{d_{i1}^{ROL}\}}\exp(u_{ij}/\sigma)}\times\ldots\times\frac{\exp(u_{id_{iR_i}}/\sigma)}{\sum_{j\in\mathcal{J}\setminus\{d_{ik}^{ROL}\}_{k=1}^{R_i-1}}\exp(u_{ij}/\sigma)} \tag{7}$$

The program utility $u_j(S_i, \tau_i, d_{ij})$ for $j \in \mathcal{J}$ is thus identified up to scale using the ROLs, i.e. we identify $\tilde{u}_j(S_i, \tau_i, d_{ij}) \equiv \frac{1}{\sigma}u_j(S_i, \tau_i, d_{ij})$. Without loss of generality, we normalize the utility of an arbitrary reference alternative to be equal to zero.[21]

Second-stage payoffs and scale parameter. As described above, the second stage of our framework corresponds to a dynamic discrete choice model. While state transitions are identified non-parametrically, identifying the second-stage payoffs requires additional restrictions. This includes specifying the distribution of the preference shocks, fixing the discount factor, and normalizing the utility of one alternative in each state (Magnac & Thesmar, 2002). We assume that preference shocks are drawn independently from a mean-zero Extreme Value Type 1 distribution, and also implicitly set in our framework the discount factor to one.[22]

Under these assumptions, the share of students who choose action k in round $t \in \{1, 2\}$ given the information set Ω_{it}, $\Pr(d_{it}^{DDC} = k|\Omega_{it})$, has the following closed-form expression:

$$\Pr(d_{it}^{DDC} = k|\Omega_{it}) = \frac{\exp(v_{ikt})}{\exp(v_{i1t}) + \exp(v_{i2t}) + \exp(v_{i3t})} \tag{8}$$

Note that the choice problem stops when students choose one of the terminal actions (namely accept, $k = 1$, or drop out, $k = 3$). In the last round ($t = 3$), the model becomes static as students can only choose between these two options, with:

$$\Pr(d_{i3}^{DDC} = k|\Omega_{i3}) = \frac{\exp(v_{ik3})}{\exp(v_{i13}) + \exp(v_{i33})} \tag{9}$$

Mapping the choice probabilities of this static choice problem into the utility functions, we

[21] In practice, this corresponds to a hypothetical Bachelor-STEM program with other characteristics (such as distance) set to zero.

[22] As the different APB admission stages rapidly follow each other - with two to three weeks between consecutive rounds - setting the annual discount factor to a lower value (such as .95) does not make any substantial difference.

have:

$$\ln \Pr(d_{i3}^{DDC} = 1|\Omega_{i3}) - \ln \Pr(d_{i3}^{DDC} = 3|\Omega_{i3}) = v_{i13} - v_{i33}$$
$$= \sigma \tilde{u}_{j_3}(S_i, \tau_i, d_{ij_3}) + w_{j_3}(S_i, \tau_i) - u_{03}(S_i, \tau_i). \tag{10}$$

We now discuss the identification of σ, the scale of the shock on the perceived utility when students rank alternatives in Stage 1. Consider the distance between student i and program j_3, d_{ij_3}, which is excluded from u_{0t} and $w_{j_3}(S_i, \tau_i)$, and for which we assume that $\frac{\partial \tilde{u}_{j_3}(S_i,\tau_i,d_{ij_3})}{\partial d_{ij_3}} \neq 0$. Taking derivatives with respect to the distance to the program and rearranging yields:

$$\sigma = \frac{\partial(\ln \Pr(d_{i3}^{DDC} = 1|\Omega_{i3}) - \ln \Pr(d_{i3}^{DDC} = 3|\Omega_{i3}))/\partial d_{ij_3}}{\partial \tilde{u}_{j_3}(S_i, \tau_i, d_{ij_3})/\partial d_{ij_3}}. \tag{11}$$

where the choice probabilities and the normalized utility $\tilde{u}_{j_3}(S_i, \tau_i, d_{ij3})$ are identified from students' choices in the last round and the ROLs, respectively. It follows that the ratio on the right-hand side of Equation (11) and thus σ are, in turn, identified. Key to this identification argument is the assumption that the perceived marginal (dis-)utility associated with enrolling farther from home remains constant between the application stage and the last admission round, conditional on the other program characteristics. These characteristics include, in particular, indicators for whether the program is located in the same catchment area as the student's home and whether it is based in Paris. Such controls allow us to account for the possibility that the value of certain location-specific features—typically unrelated to distance per se—may evolve over the course of the admission procedure, for instance due to housing market pressures.[23]

From this, Equation (10) can be used to identify the difference between the change in the utility derived from accepting the offer received in round 3 with respect to the perceived associated utility at the application stage, $w_{j_3}(S_i, \tau_i)$, and the utility of dropping out, $u_{03}(S_i, \tau_i)$. Under the assumption that the term capturing time-varying preferences for programs, $w_{j_3}(S_i, \tau_i)$, depends only on the characteristics of the offer received and its interactions with student characteristics, we can evaluate the difference for j_3 corresponding to the reference alternative to separately identify the utility of dropping out. Identification of $w_{j_3}(S_i, \tau_i)$

[23]Housing market pressures are especially acute in Paris, where the mismatch between the supply and demand for student accommodation is particularly severe (Cour des Comptes, 2025).

follows.

The other components of the model can then be identified by proceeding by backward induction, taking into account the expected value of behaving optimally in the future. This is facilitated by the closed-form expression resulting from the mean-zero type 1 extreme value distribution assumption on the preference shocks, which yields (with the convention that $v_{i23} = -\infty$):

$$\bar{V}_{it+1}(\Omega_{it}, j_{t+1}) = \ln(\exp(v_{i1t+1}) + \exp(v_{i2t+1}) + \exp(v_{i3t+1})) \tag{12}$$

Substituting Equation (12) into Equation (4) allows us to write the conditional value functions in $t = 2$, up to the conditional choice and admission probabilities, the utility parameters and state transitions. We can then proceed in an analog way for $t = 1$.[24] In rounds 1 and 2, waiting costs (ω_i) are key parameters that affect the decision to delay. As mentioned earlier, these costs are modeled based solely on individual characteristics and are identified from the baseline probability that a student chooses to wait for a better offer, regardless of the offer held. Conceptually, they capture in particular the disutility students derive from facing uncertainty with respect to their assignment outcome, compared to being assigned to the benchmark program. In contrast, time-varying preferences for programs allow the value of a given offer to depend on the round at which it is received. Changes in preferences relative to the application stage are identified by systematic variation in students' acceptance decisions across rounds, as a function of offer attributes and their interaction with student characteristics. Finally, variation across admission rounds in the utility of dropping out is identified from the systematic differences across rounds in drop out shares.

Unobserved heterogeneity. We now discuss the identification of the distribution of the heterogeneity types τ_i, which are unobserved to the econometrician. Under our modelling assumptions, the unobserved heterogeneity types are the only source of persistent unobserved heterogeneity that generates correlation between decisions made at the ROL-submission stage and the decisions at each stage of the dynamic model. In particular, in the first stage of the model, type-specific parameters in the perceived utility function are informed by two main types of variation. First, they rationalize observed propensities that are unexplained by observed applicant characteristics, to include programs that share similar characteristics

[24]Note that not every alternative is always available to each applicant, which is equivalent to setting the value of the alternative at that round to $v_{ikt} = -\infty$. For example, students who receive an offer from their top-ranked alternative are not allowed to choose *delay*; and a student without an offer cannot choose *accept*.

within one's ROL. That students generally list multiple programs at the application stage generates a source of variation, akin to a panel dimension, that is key to the identification of the distribution of unobserved heterogeneity types. Second and importantly, because unobserved types generate differences in the intensity of preferences for programs, type-specific parameters are also informed by different probabilities to delay acceptance conditional on the applicant characteristics and the characteristics not only of the offered programs, but of the higher-ranked programs in the ROL as well.

In the dynamic portion of the model, the waiting cost, the time-varying preferences for the program characteristics as well as the utility of dropping out are also allowed to vary across heterogeneity types. The dynamics of the model play an important role in identifying the corresponding type-specific parameters. For example, students with low unobserved waiting costs may choose to participate to the three admission rounds, receiving their third- and second-best offers in rounds 1 and 2, respectively, while ultimately deciding to drop out in round 3. In addition, unobserved heterogeneity in the utility of dropping out would help rationalize the co-existence of students, with similar observable characteristics, who drop out from the platform after being admitted to their top-ranked program, and students who decide to accept an admission offer from their lowest-ranked program.

5.2 Parameterization

In practice, we use for estimation a flexible parametric structure. These parametric restrictions yield substantial precision gains and allow us to use the rich set of available discrete and continuous observables that capture student heterogeneity.

Utility over programs. We parameterize the function representing student i's perceived utility for program $j \in \mathcal{J}$ at the time of submitting their ROL as follows:

$$u_j(S_i, \tau_i, d_{ij}) = z_j' \phi_{1\tau_i} + z_j' \Phi_2 x_i + \ell_j' \phi_3 + c_{ij} \ell_j' \phi_4 + \phi_5 c_{ij} + \phi_6 d_{ij} \tag{13}$$

where z_j is a vector of dummy variables corresponding to program j's type (Bachelor program, vocational, technical, two-year prep school, and other) and dummy variables corresponding to program j's major (STEM, Economics/Law, Humanities, Production, and Services).[25]

[25] We use both STEM and Production as benchmark categories as STEM does not appear in the vocational and technical programs, while production does not appear in the other programs. Bachelor is used as a

Φ_2 is a matrix of parameters of appropriate dimension, while parameter vectors appear in lowercase, such as ϕ_3. We allow preferences for z_j to vary with both observed (x_i) and unobserved (τ_i) student characteristics. In particular, x_i is a vector that includes student i's gender, socioeconomic status, scholarship status, high school track and its interaction with high school GPA. The latter two variables can be thought of as correlates of academic ability, as students who enroll in academic track are positively selected on prior academic achievement. We also control for variables that capture the characteristics of the location of the program j. ℓ_j is a vector that includes the average rent of the location of program j and dummy variables for whether program j is located in an urban area and in Paris.[26] c_{ij} is a dummy variable equal to one if the program is located in the same catchment area as student i. d_{ij} is the distance in kilometers between i's home and the location of program j. For the sake of brevity, we defer the parameterization of $w_{j_t}(S_i, \tau_i)$, which captures the possible change in preferences for programs across periods, to Appendix B.

Waiting costs. We parameterize the utility waiting cost as follows:

$$-\omega(S_i, \tau_i) = \alpha_{1\tau_i} + x_i'\alpha_2. \tag{14}$$

Utility of dropping out of the platform. Finally, the utility of dropping out of the platform is given by:

$$u_{0t}(S_i, \tau_i) = \delta_{0t} + \delta_{1\tau_i} + x_i'\delta_2. \tag{15}$$

Under this specification, waiting costs and the outside option utility may differ across applicants, as a function of both observed characteristics and unobserved type. The intercept of the utility of dropping out of the platform is also allowed to vary across rounds, capturing potential changes in outside options over the course of the admission process.

State transitions. To solve the dynamic model, students take into account the probability to receive an offer in the next round, $\Pr(j_{t+1} = j'|\Omega_{it})$. We use a parametric, but flexible specification by estimating a logit model that predicts the probability to improve the current

program type benchmark category.

[26] Urban areas refer to cities for which we have access to rent data, that we obtain from Century 21, as defined in Appendix A.2.

offer, $\Pr(j_{t+1} \neq j_t|\Omega_{it})$, and a conditional logit among the higher-ranked options, namely $\Pr(j_{t+1} = j'|\Omega_{it}, j_{t+1} \neq j_t)$.

The first probability, $\Pr(j_{t+1} \neq j_t|\Omega_{it})$, is allowed to depend on the student's observed characteristics S_i and unobserved type τ_i, and varies across rounds through round t-specific intercepts. The program's type and major are also allowed to affect the probability of receiving a better offer. Finally, we control for the urban dummy, rent, the rank, and the distance to the current offer, and we add controls for the number of higher-ranked programs of each type in the ROL. For the probabilities of receiving an offer from a particular (higher-ranked) program, we first predict the selectivity of a program with an index.[27] This selectivity index enters with a round-specific effect and interactions with observed characteristics S_i and heterogeneity type τ_i. We also include dummy variables for both program types and majors, as well as the urban dummy, rent, the rank and distance to the offer.

5.3 Estimation

For expositional reasons, we first discuss the estimation procedure for a specification with known heterogeneity types, before turning to the estimation with unknown types. Standard errors are obtained using a bootstrap procedure.[28]

5.3.1 Estimation with Known Types

With known types τ_i, we need to estimate the perceived utility of being matched to a program, $u_j(S_i, \tau_i, d_{ij})$, the time-varying component of accepting an offer, $w_{j_t}(S_i, \tau_i)$, the value of the outside option, $u_{0t}(S_i, \tau_i)$, and the waiting costs, $\omega(S_i, \tau_i)$. Moreover, we need to estimate the state transitions $\Pr(j_{t+1} = j'|\Omega_{it})$ from the data.

[27] To do this, we estimate a logit where the dependent variable is equal to one if the student was admitted to the program in the first round, and compute a program's selectivity index as 1- the associated predicted latent variable. We restrict the estimation sample to the student-program pairs such that i) the student applied to the program, and ii) for which we observe whether the program admitted the student. In practice, ii) implies that we restrict the sample to programs ranked weakly above the one from which the student received an offer in the first round, as we do not observe whether students would have been rejected from programs that are ranked below. For the production and services majors, we allow for different effects in technical and vocational programs. The Economics/Law, STEM and Humanities majors are allowed to have different effects in prep-school, Bachelor and other programs.

[28] We draw 50 samples of students with replacement, re-estimate every part of the model for each of the bootstrap samples and report the standard deviation of the estimates. As in De Groote (2025), we do not rerun the EM algorithm used to uncover the unobserved types.

Let θ denote all the model parameters to be estimated. We can write the likelihood function for the model, where each individual's contribution to the likelihood is given by:

$$L_i(\theta) = L_{1i}^{ROL}(\theta_1) \prod_{t=1}^{2} (L_{it}^{TRANS}(\theta_2) L_{it}^{DDC}(\theta_1, \theta_2, \theta_3)) L_{i3}^{DDC}(\theta_1, \theta_2, \theta_3)$$

with $\theta = (\theta_1, \theta_2, \theta_3)$. $L_{1i}^{ROL}(\theta_1)$ is given by the probability of the observed ROL (Equation (7)), where θ_1 are the utility parameters of each program, up to scale. $L_{it}^{TRANS}(\theta_2)$ is the contribution of the state transitions in period t, with θ_2 the associated parameters. Finally, $L_{it}^{DDC}(\theta_1, \theta_2, \theta_3)$ is given by the choice probabilities in each round (Equations (8)-(9)), where θ_3 are the remaining parameters associated with the decisions to accept, delay or drop out. These parameters include the scale of the first stage shock (relative to the scale of utility) σ, the parameters of the time-varying component of accepting an offer, the waiting cost parameters, and the parameters governing the utility of dropping out.

The log-likelihood function is additively separable in its different components, with the individual contribution being given by:

$$l_i(\theta) = l_{1i}^{ROL}(\theta_1) + \sum_{t=1}^{2} (l_{it}^{TRANS}(\theta_2) + l_{it}^{DDC}(\theta_1, \theta_2, \theta_3)) + l_{i3}^{DDC}(\theta_1, \theta_2, \theta_3).$$

It follows from this representation that we can obtain consistent estimates by sequential estimation. Namely, we first estimate θ_1 from a rank-ordered logit model on the submitted ROLs.[29] We estimate θ_2 from the conditional logit models that predict state transitions. We then estimate the remaining parameters θ_3 in the dynamic choice model, taking as given the estimated values of θ_1 and θ_2. We detail below the estimation of the dynamic model of student enrollment decisions.

CCP estimation. In order to estimate θ_3 using a full solution method, one would need to solve the second stage of the model for each value of the state. This is cumbersome as the state space includes every option that student i included in its ROL. We rely instead on Conditional Choice Probability (CCP) estimation.

In our model, dynamics enter through the choices allowing a student to stay on the

[29] Since the choice set of students is very large, we exploit the properties of the logit probabilities and estimate the model by random sampling from the choice set, as discussed in Train (2009, p. 65). In practice, we sample 450 alternatives out of the total set of 10,150.

platform in the following round ($k = 2$). We deal with the expected value of behaving optimally in the next round by rewriting the conditional value function of $k = 2$ following Hotz & Miller (1993) and Arcidiacono & Miller (2011). In particular, we can rewrite the ex ante value function (Equation (12)) as a function of the conditional value function of dropping out ($k = 3$), a terminal action that is always available, and the CCP of that action:

$$\bar{V}_{it+1}(\Omega_{it}, j_{t+1}) = u_{0t+1}(S_i, \tau_i) - \ln \Pr(d_{it+1}^{DDC} = 3|\Omega_{it}, j_{t+1})$$

Note that in this context with a terminal action, the finite dependence property trivially holds (Arcidiacono & Miller, 2011), with the right-hand side not involving any future value term.

We can then use this to rewrite the conditional value function associated with the option to delay ($k = 2$):

$$\begin{aligned} v_{i2t} &= -\omega(S_i, \tau_i) + \sum_{j' \in \mathcal{R}_i^{j_t} \cup \{j_t\}} \Pr(j_{t+1} = j'|\Omega_{it}) \left(u_{0t+1}(S_i, \tau_i) - \ln \Pr(d_{it+1}^{DDC} = 3|\Omega_{it}, j_{t+1})\right) \\ &= -\omega(S_i, \tau_i) + u_{0t+1}(S_i, \tau_i) - \sum_{j' \in \mathcal{R}_i^{j_t} \cup \{j_t\}} \Pr(j_{t+1} = j'|\Omega_{it}) \ln \Pr(d_{it+1}^{DDC} = 3|\Omega_{it}, j_{t+1}) \end{aligned}$$

where the last line follows from $\sum_{j' \in \mathcal{R}_i^{j_t} \cup \{j_t\}} \Pr(j_{t+1} = j'|\Omega_{it}) = 1$. Using these conditional value functions, we can estimate the parameters θ_3 without solving the full dynamic problem by estimating the CCPs in a first step—i.e., $\Pr(d_{it+1}^{\text{DDC}} = 3 \mid \Omega_{it}, j_{t+1})$ for $t = 1, 2$. This approach yields an estimator analogous to that of a static discrete choice model with a pre-determined correction term.[30]

5.3.2 Estimation with Latent Types

Let there be M types $\tau \in \{1, \ldots, M\}$ with probability of occurring π_τ. Accounting for type-specific unobserved heterogeneity breaks down the additive separability of the log-likelihood, which is now written as:

[30] We predict CCPs of dropping out using a flexible binary logit. We include the observed and unobserved characteristics of the student, that we interact with characteristics of the current offer. We also include the numbers of programs ranked higher of different types. For the characteristics of the current offer, we take into account distance, the urban dummy, rent, the rank of the offer, and the selectivity index.

$$l_i(\theta, \pi) = \ln \left[\sum_{\tau=1}^{M} \pi_\tau L_{1i\tau}^{ROL}(\theta_1) \prod_{t=1}^{2} (L_{it\tau}^{TRANS}(\theta_2) L_{it\tau}^{DDC}(\theta_1, \theta_2, \theta_3)) L_{i3\tau}^{DDC}(\theta_1, \theta_2, \theta_3) \right] \tag{16}$$

with an additional vector of unknown type proportion parameters to estimate: $\pi = (\pi_2, ..., \pi_M)$ with $\pi_1 = 1 - \sum_{\tau=2}^{M} \pi_\tau$. The likelihood components ($L_{1i\tau}^{ROL}, L_{it\tau}^{TRANS}, L_{it\tau}^{DDC}$) are indexed by τ to reflect the fact that they depend on heterogeneity types.

We adopt the estimation approach of Arcidiacono & Miller (2011), which adapts the EM algorithm to this context, allowing us to restore the additive separability of the likelihood function. The procedure is implemented as follows: we first fix the number of types M and initialize the parameter vector θ. Using these starting values, we compute the probability that each individual i belongs to each type τ and estimate the corresponding population type probabilities π. We estimate the CCPs and the model parameters treating types as known, using the individual posterior type probabilities as weights. The new set of estimates for θ is then used to update the type probabilities. This process is repeated until convergence of the log-likelihood function.

In practice we implement the two-stage procedure of Arcidiacono & Miller (2011) that approximates in an initial step the decision process with a reduced form, replacing $L_{it\tau}^{DDC}$ by a reduced-form type-specific choice likelihood (see Arcidiacono et al., 2025, for a recent application of this two-stage estimator).[31] We estimate in the first stage the parameters of the ROL submission stage (θ_1), the state transition parameters (θ_2), the CCPs and the posterior probabilities of belonging to any given heterogeneity type. We then estimate in the second stage the structural parameters θ_3 in a similar fashion to the case with known types discussed above, with a weighted conditional logit using the posterior type probabilities as weights.[32]

[31] We estimate a conditional logit on the three options available by letting all observable student characteristics, unobserved heterogeneity types, and characteristics of the offer received (including program type, major, and location-specific characteristics) have choice-specific effects. Moreover, we allow for different intercepts by round.

[32] In practice, to speed up the estimation, we work with a smaller sample for the first stage of the estimator (9,454 students and rank-ordered lists up to rank 5), and then calculate posterior type probabilities for a larger sample (63,850 students) to obtain more precise estimates for the structural parameters of the dynamic model.

6 Estimation Results

In this section, we discuss some key estimated parameters related to program utility and waiting costs. All of the parameter estimates for the utility, waiting cost, graduation model, and transition probabilities are reported in Appendix C.

Students' preferences over programs. The findings generally align with intuition and prior research. In particular, students value proximity to home, as evidenced by the negative coefficient on distance and the positive non-linear effect of staying within their residential catchment area. We also observe substantial heterogeneity in preferences across both student observed characteristics and unobserved type.[33] Graduates from the academic high school track with a humanities or social sciences major and average GPA tend to prefer Bachelor's programs over two-year vocational programs. This preference corresponds to a utility gain equivalent to reducing the distance to the enrollment program by 155 km. These students also exhibit stronger preferences for programs in humanities and economics/law relative to STEM fields, corresponding to utility gains equivalent to a 40 km and 160 km reduction in distance from home, respectively. As GPA increases, non-Bachelor (selective) programs become more desirable. We also find that students from vocational and technological high school tracks prefer two-year vocational post-secondary programs over Bachelor's.

Outside of the high school track of the student and the GPA, demographic characteristics also shape their preferences. In particular, female students have a stronger preference for non-STEM fields over STEM fields compared to male applicants, consistent with the well-documented under-representation of women in STEM fields and careers (Kahn & Ginther, 2017; Saltiel, 2023; Humphries et al., 2024). All else equal, lower-SES students display stronger preferences for Bachelor's programs compared to their higher-SES peers. We also find substantial unobserved heterogeneity in students preferences. In practice, we set the number of unobserved student type, M, to be equal to 2. We find in particular that students of unobserved type 2 have a stronger preference for Bachelor programs compared to type 1 students, with 53% of the sample estimated to be type 2 (Table C-8).

Regarding the time-varying component of student preferences, Tables C-5 to C-7 show

[33] Heterogeneity is measured relative to a benchmark group defined as high-SES, male students not eligible for a scholarship, enrolled in the academic high school track with a humanities or social sciences major, and with unobserved type 1.

that program-type preferences substantially shift between the ROL-submission and the offer-acceptance stages. In particular, prep-school programs appear to be more desirable at the time of offer acceptance—especially for high-SES students from the academic track—than they were when students initially submitted their ROLs. Similarly, vocational and technical programs gain appeal at the acceptance stage, particularly among female students and those enrolled in the technological high school track. High-SES students also show an increased preference for programs located in Paris in the first two rounds of offers relative to the ROL-submission stage, although this pattern does not persist into the third round. Taken together, these patterns highlight the importance of allowing preferences for different types of programs to vary over the course of the application and admission process.

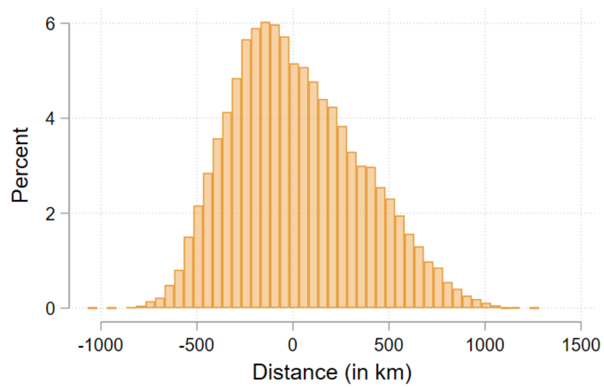
Utility from dropping out. Table C-8 shows substantial heterogeneity in the utility students derive from dropping out of the platform. In particular, low-SES students and those eligible for a scholarship experience a significantly higher disutility from exiting the centralized system compared to more advantaged peers, suggesting that the latter may have access to more attractive outside options. In contrast, female students exhibit a higher utility from dropping out, which is consistent with the fact that institutions operating off-platform include an important number of nursing and paramedical programs—fields typically enrolling more female than male students.

We also observe that students in the academic track with a science major face greater disutility from dropping out than those majoring in humanities or social sciences. This pattern may reflect the availability of more attractive outside options available to the latter, such as business schools recruiting off-platform and double-major Bachelor programs in humanities.[34] In contrast, students in the vocational and technological tracks appear to face lower disutility from dropping out, possibly because they are more likely to transition directly into the labor market upon high school graduation.

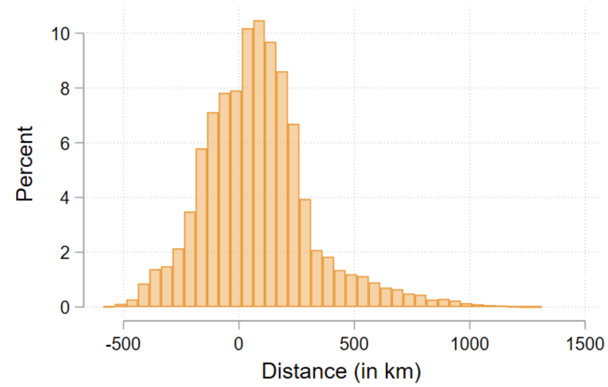
Finally, the value of dropping out of the platform also varies over the course of the admission process. It is associated, on average, with a disutility which is lower in round 3 than in rounds 1 and 2 of the offer-acceptance stage, consistent with off-platform institutions

[34] Two-thirds of business schools that recruit students directly after high school—programs primarily aimed at those in the social sciences track—operate outside the platform. In contrast, only 12% of engineering schools offering post-secondary entry, which are primarily intended for students in the sciences track, are off-platform (Table A-1).

Figure 3: Illustrating the Magnitude of Waiting Costs



(a) Waiting Costs vs. Preferences over Majors



(b) Waiting Costs vs. Preferences over Types of Programs

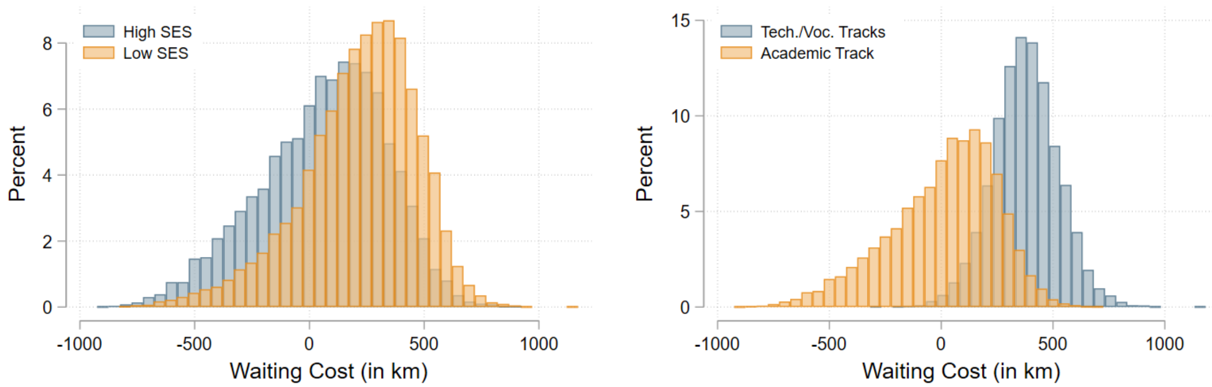
Notes. Panel (a) shows the distribution of the difference between the absolute value of students' valuation of STEM vs humanities and their individual waiting costs, both expressed in distance-increase-equivalent (in km). It focuses on students for whom choosing *delay* is a possibility in round 1, i.e. those with an offer that is not from their top-ranked program. For reference, Figure C-1 shows the distribution of waiting costs at the end of round 2, which is very similar to the one for round 1. Panel (b) is similar to Panel (a) but compares waiting costs to preferences for program types rather than majors. Specifically, it shows the distribution of the difference between the absolute value of students' valuation of Bachelor's vs prep-school programs, and their individual waiting costs, both expressed in distance-increase-equivalent (in km).

releasing their admission offers later in the summer.

Waiting costs. Waiting costs are both substantial and highly heterogeneous across students. The median estimated waiting cost is equivalent to the disutility associated with a 172km-increase in the distance between one's home and post-secondary program. As a reference to better evaluate this magnitude, note that the average difference in utility between students' first- and second-ranked program is equivalent to a reduction in the home-university distance of 103 km, and that the average distance between a student's home and their assigned program is 60 km only (Table A-2).

Figure 3 illustrates the magnitude of waiting costs relative to other key dimensions of college decisions. Panel (a) shows the distribution of the difference between the absolute value of students' valuation for programs in STEM versus humanities, and their individual waiting costs, both expressed in kilometer-equivalent terms. A negative value indicates that the disutility from waiting exceeds the utility gain associated with switching to a preferred major, holding other factors constant. The median of this distribution is -10km, which means that for more than half of the students, utility gains from receiving an offer from a program in a more preferred major would be more than fully offset by the cost of delaying acceptance

Figure 4: Heterogeneity in Waiting Costs



(a) Waiting Costs by SES

(b) Waiting Costs by High School Track

Notes. This figure shows the distribution of estimated waiting costs across SES (Panel (a)) and across high school tracks (Panel (b)). The group "high SES" comprises high-SES and middle-high-SES students; the group "low SES" comprises middle-low and low-SES students. We focus on students who have the possibility to *delay* in round 1, i.e. those with an offer outside of their top-ranked program. For reference, Figure C-1 shows the distribution of waiting costs at the end of round 2, which is very similar to the one for round 1. Waiting costs are expressed in distance-increase-equivalent (in km).

by one round. Panel (b) presents a similar comparison, this time between waiting costs and preferences over program types. Specifically, it shows the distribution of the difference between students' absolute valuation of Bachelor's versus prep-school programs and their waiting costs. In contrast to Panel (a), we find that preferences over program types exceed waiting costs for most students: the median gap is 72 kilometers, indicating that students tend to value switching to a preferred program type more than they dislike waiting.

We also find substantial heterogeneity in waiting costs across students. In particular, waiting costs vary substantially across socio-economic groups, as displayed in Panel (a) of Figure 4. The median waiting cost is equivalent to a large—248km—increase in enrollment distance for lower-SES students against 92km for higher-SES students. This is consistent with the idea that disadvantaged students may not be able to benefit from the option value of waiting for a better match, for example due to the need to secure affordable housing or find a student job before the academic year begins. This may also reflect a weaker parental pressure, for low-SES students, to pursue the best possible offer on the platform. Similarly, we observe that students in the technological and vocational high school tracks face higher waiting costs than students in the academic track (Panel (b)). While some of this is mediated by SES, with students from disadvantaged background being less likely to enroll in an academic track, this large heterogeneity suggests that additional channels are at play. In particular, high school students in the technological and vocational tracks may not benefit as much as those enrolled in the academic track from teachers' guidance and push to delay acceptance in order to optimize their higher education match.[35]

7 The Value of Sequential Admissions

In this section, we evaluate the impact of the sequential admission mechanism in place as part of the APB system on students' educational outcomes and welfare, relative to a standard single-round mechanism. To do so, we conduct a counterfactual analysis that leverages the model and parameter estimates discussed above.

7.1 Implementation

We use a counterfactual exercise to quantify the impact of sequential admission mechanisms on students' educational outcomes, in particular graduation rates and on student welfare. To this end, we compare outcomes and welfare under the status quo sequential mechanism (denoted by SQM) and under a standard one-round mechanism (denoted by 1RM). Under the 1RM, students submit their rank-ordered lists (ROLs) of programs and receive offers exactly as in the first round of the SQM. However, in contrast to the SQM, they do not have the option to delay their decision in the hope of receiving a higher-ranked offer later: they must either accept the offer or drop out of the platform, with the value of each option given by Equations (3) and (5), respectively. For both admission mechanisms, we simulate outcomes using the observed ROLs and first-round offers, consistent with our model.

In particular, to predict the value associated with each available option and simulate students' decisions under the 1RM, we draw ϵ_{ikt} shocks for $t = 1$. Under the SQM, students make their round-1 decisions based on these same $t = 1$ shocks and their expected continuation value. Students who proceed to the next round receive new offers according to the estimated state-transition process (see Appendix Tables C-17 and C-18). They then draw new ϵ_{ikt} shocks for $t = 2$, and the process repeats until the end of round 3 when a terminal decision needs to be made. Given matches under each mechanism, we predict graduation outcomes using our estimates for Equation (6).

[35]Our estimates reveal the net effect of the cost of having to wait and any preference to procrastinate by not deciding on the on-platform offer right away. If the latter dominates, this can lead to a negative waiting cost which we find for a significant share of the students who are graduating from the academic track.

7.2 Results

We now present results that describe the impact of the three-round sequential admission mechanism on graduation rates and student welfare. Our analysis focuses on students who do not receive an offer from their top-ranked program in the first round of the APB process—that is, students who have the opportunity to delay acceptance in the hope of receiving a higher-ranked offer in one of the subsequent rounds of the admission process.[36]

Table 4: Final On-Platform Decision

	Sequential Mechanism			
	Drop Out	Accept		*Total*
One-Round Mechanism				
Drop Out	.08	.10		*.18*
		Same Match	Higher Rank	
Accept	.07	.64	.10	*.81*
Total	*.15*	*.84*		*1.00*

Notes. This table focuses on students with no top-ranked offer in round one. It presents the transition in match status across mechanisms.

Effects on acceptance decisions. We start by examining the effect of the SQM on students' on-platform acceptance decisions. Table 4 compares students' match outcomes across the two mechanisms. First, we find that the SQM leads to a decrease in the share of students who do not accept any offer on the platform: this share falls from 18% under the 1RM to 15% under the SQM. In particular, 56% of the applicants not accepting any offer in the 1RM (representing 10% of all applicants) see their match outcome changed by the SQM, as they accept an offer through the centralized procedure —they *gain a match*.[37] Two mechanisms drive this pattern. On the one hand, 65% of the students gaining a match thanks to the SQM did not receive any offer through the 1RM. The redistribution of declined seats through the sequential procedure allows these students to get an offer from an on-platform program which they eventually accept. On the other hand, 35% of the students gaining a match in the SQM also receive an offer in the 1RM, but decide to reject it. In contrast, in the SQM, they delay

[36]These students represent 46.8% of our sample. Note also that our analysis does not consider high school graduates who do not participate in the centralized assignment process.

[37]Note that about 9% of applicants who accept a match under the 1RM do not under the SQM. These students accept their offer in the 1RM while they delay in the SQM, before ultimately dropping out, which is consistent with the value of their outside option that varies across rounds.

their decision to wait for another offer, and eventually accept a match in a later round.

Second, and importantly, a significant share of the students accepting an on-platform offer with the 1RM also benefit from the SQM. Indeed, 12.3% of them receive and accept a higher-ranked offer under the SQM. These students *improve their match* thanks to the dynamic redistribution of declined seats.

We further examine students' academic trajectories under the two mechanisms, distinguishing between those who *gain a match* and those who *improve their match* under the SQM relative to the 1RM.

Table 5: Graduation Rates Across Mechanisms for Those Who Gained a Match

	Sequential Mechanism		
One-Round Mechanism	Do Not Graduate	Graduate	*Total*
Do Not Graduate	.38	.26	*.64*
Graduate	.02	.34	*.36*
Total	*.40*	*.60*	*1.00*

NOTES. This table focuses on students who gain a match, i.e. they accept an offer under the sequential mechanism, but not under the one-round mechanism. It compares graduation outcomes across the two mechanisms.

Mechanism 1: Broader access under the SQM. The academic trajectories of students who gain a match under the SQM relative to the 1RM are shown in Table 5. Under the SQM, 60% of them eventually graduate from the higher education system. Slightly more than half of these graduates would obtain a degree under the 1RM as well, despite the fact that they did not accept an on-platform offer. Most of these students graduate from an off-platform program.[38] Although these students graduate under both mechanisms, we find that 41% of them graduate from a program of a different type and/or major under each mechanism.

The rest of the students graduating under the SQM would leave the higher education system without a degree under the 1RM. Hence, by redistributing on-platform vacancies, the SQM allows students to match to an on-platform program, which eventually affects their graduation status. These students represent the majority (65%) of the students brought to graduation by the SQM.

[38]Note that our graduation model is estimated using data from students enrolled in the French higher education system, implying that we can track the trajectory of students enrolling off-platform, as well as the trajectory of students declining an on-platform offer in 2015, but ultimately enrolling on-platform in the following years. Some of the students who would obtain a degree under the 1RM without receiving an initial on-platform offer belong to the latter group.

Table 6: Graduation Rates Across Mechanisms for Those Who Improved Their Match

	Sequential Mechanism		
One-Round Mechanism	Do Not Graduate	Graduate	*Total*
Do Not Graduate	.22	.09	*.31*
Graduate	.03	.67	*.70*
Total	*.25*	*.76*	*1.00*

Notes. This table focuses on students who have a match under both mechanisms, but accept a higher-ranked offer under the sequential mechanism. It compares graduation outcomes across the two mechanisms.

Before turning to this second mechanism, note that very few (about 2%) of the students who gain a match under SQM see their graduation outcome adversely affected by the SQM, that is, do not graduate under SQM while they do under 1RM.

Mechanism 2: Improved offers under the SQM. As seen in Table 4, 10% of applicants obtain an on-platform match in both procedures but eventually accept a higher-ranked offer in the SQM. The graduation outcomes of those who receive an improved offer are shown in Table 6. We find that these students also benefit from the SQM, as it allows them to match to programs they prefer and from which they are more likely to eventually graduate. 9% of the students who improve their match thanks to the SQM would exit the higher education system without a degree under the 1RM. While 67% of students with improved offers graduate under both mechanisms, we also note that we find significant effects on their graduation program as 22% of them graduate in a different type and/or major. Similarly to the group of applicants who gain a match, only 3% of the students who improve their match do not graduate under the SQM while they do under the 1RM.

Overall effect on graduation and drivers. Overall, we find that the SQM reduces the share of students exiting the higher education market without a degree by 2 percentage points compared to the 1RM, which corresponds to a 5.4% decrease in the drop out rate (Table 7). It is interesting to note that this effect is close in magnitude to the impact of incorporating universities previously operating off-platform into the centralized platform, as identified through an event-study in Chile (Kapor et al., 2024)—an intervention that may in some settings be politically or logistically difficult to implement. The change in the centralized admission mechanism we consider here can in principle be implemented at a low cost, through a change in the allocation algorithm.

Table 7: Graduation Rates Across Assignment Mechanisms

	Sequential Mechanism		
One-Round Mechanism	Do Not Graduate	Graduate	*Total*
Do Not Graduate	.33	.04	*.37*
Graduate	.02	.61	*.63*
Total	*.35*	*.65*	*1.00*

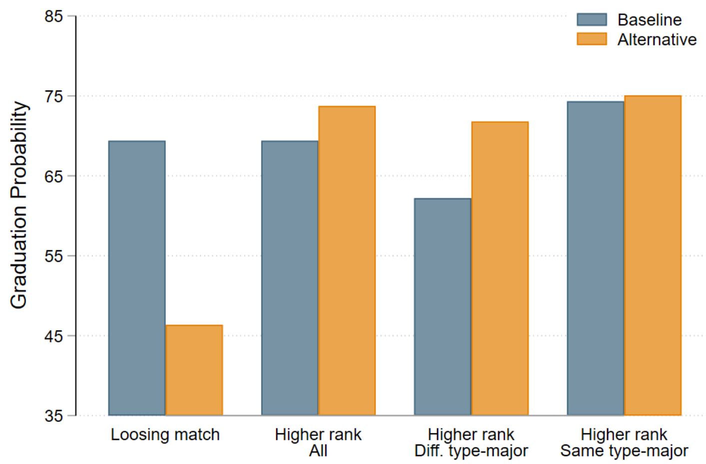
Notes. This table focuses on students with no top-ranked offer in the first round of the sequential mechanism. It compares graduation outcomes across the two mechanisms.

Figure 5 sheds light on the mechanisms that lead students who gain or improve their match to graduate at higher rates. The first set of bars isolates the effect of obtaining a match through the platform. Focusing on students who successfully match on the platform, it compares their average predicted probability of graduation (blue bar) to a scenario in which the same students had not matched on the platform (orange bar). We find that the graduation rate of these students would have been reduced by as much as 24 percentage points. Matching on platform is particularly crucial for the post-secondary graduation outcomes of students enrolled in the vocational and technological high school tracks—had they not secured a match on platform, matched vocational- and technological-track students would be 55% less likely to graduate from the higher education system; against 24% for academic-track students (Figure D-1 in Appendix).

The second set of bars in Figure 5 illustrates the effect on graduation of improving one's on-platform match by one rank. The blue bar repeats the average graduation rate of those matching on platform. The orange bar now shows the predicted average graduation probability for the same students had they matched one rank higher on their ROL. The last two sets of bars decompose this effect between those for whom the one-rank-up program differs from the baseline match in major, type, or both; and those for whom the one-rank-up program has the same major and type as the baseline match. It shows that graduation gains following an improvement in the match are entirely driven by a better match between the program and student characteristics, rather than by a pure rank effect.[39] The effect of matching one rank higher on the graduation probability is about twice as large for matched vocational- and technological-track students compared to academic-track students (8 vs 3.6 percent increases,

[39] This is not hard-wired in the model as our graduation model does allow for such a pure rank effect. Overall, 46% of students who improve their match accept an offer from a program with different type and/or major in the SQM as compared to 1RM (Appendix Table D-1).

Figure 5: Role of being matched and of matched rank on graduation probability



NOTES. This figure illustrates how accepting an on-platform offer—and the rank of that offer—affects students' likelihood of graduating from the higher education system. Blue bars represent baseline graduation probabilities; orange bars show predicted probabilities after manipulating the offer received for the same students. The first two sets of bars present results for the full sample. The third set breaks down outcomes for students whose higher-ranked program differs in major, program type, or both. The fourth set focuses on students who would instead be matched to a program that is observationally equivalent in both major and type.

respectively, in Figure D-1).

Heterogeneity across students. Who benefits from the SQM? Table 8 examines the characteristics of students who either gain a match or improve their assignment, as well as those who, as a result, go on to graduate from higher education. Vocational and technological high school graduates are overrepresented among students who gain a match (compare Column (4) to Column (2) in Table 8), with a similar pattern observed for low-SES students. This reflects the fact that these groups are disproportionately more likely to be without a first-round offer (see Appendix Table D-2). In contrast, students from the academic track and those from medium- to high-SES backgrounds are more likely to improve the quality of their match under the SQM. Conditional on gaining or improving their match, vocational graduates—and to a lesser extent, technical students—are also the most likely to gain graduation from higher education (see Column (5) vs. (4) and Column (7) vs. (6)). While the expected benefits of waiting for these students appear substantial, these students also face significantly higher waiting costs (Figure 4), and they ultimately are less likely to wait than their academic-track counterparts (Column (3) vs. Column (2)).

Table 8: Student Characteristics by Change in Match Status and Graduation Outcome

	Overall	No Top-Ranked Offer	No Top-Ranked Offer & Wait	Gain Match	Gain Match & Gain Grad.	Improve Match	Improve Match & Gain Grad.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.535	0.496	0.492	0.502	0.448	0.504	0.502
With Scholarship	0.166	0.167	0.156	0.171	0.140	0.165	0.241
SES							
High	0.329	0.347	0.355	0.276	0.228	0.342	0.261
Medium-High	0.160	0.153	0.154	0.160	0.159	0.170	0.177
Medium-Low	0.292	0.281	0.280	0.314	0.341	0.284	0.305
Low	0.220	0.219	0.211	0.250	0.271	0.204	0.256
High-school Track							
Academic Track	0.667	0.627	0.646	0.488	0.426	0.692	0.557
Technical Track	0.218	0.238	0.225	0.273	0.285	0.219	0.330
Vocational Track	0.115	0.135	0.129	0.239	0.289	0.090	0.113
High School GPA							
Academic Track	0.139	0.095	0.129	-0.288	-0.394	0.044	-0.314
	(.975)	(.977)	(.989)	(.873)	(.723)	(.919)	(.775)
Technical Track	-0.044	-0.254	-0.253	-0.429	-0.442	-0.086	-0.368
	(.815)	(.741)	(.739)	(.702)	(.734)	(.776)	(.769)
Vocational Track	0.557	0.600	0.578	0.555	0.431	0.638	0.565
	(.497)	(.490)	(.494)	(.497)	(.497)	(.482)	(.407)
Unobserved Type							
Type 2	0.522	0.515	0.509	0.571	0.544	0.509	0.586

Notes. This table shows the characteristics of students in the estimation sample (Column (1)), who do not get an offer to their top-ranked program (Column (2)), who gain a match under the sequential mechanism (Column (3)), who both gain a match and gain graduation under the sequential mechanism (Column (4)), who accept a higher-ranked offer under the sequential mechanism (Column (5)), and who accept a higher-ranked offer and gain graduation under the sequential mechanism.

Welfare effects. We illustrate the value of allowing students to delay their decision and wait for better offers in Table 9. Specifically, we report the average difference in student welfare in the SQM relative to the 1RM as a function of their match outcomes, that is, as a function of whether they accept an offer or drop out of the platform under under each mechanism. Our focus is on student welfare—measured in distance-equivalent terms—from the perspective of the end of round 1. In the 1RM, this corresponds to the final outcome of the assignment process. Students assigned under the 1RM can either accept an offer, receiving utility $v_{i11} + \epsilon_{i11}$, or choose to drop out and receive $v_{i31} + \epsilon_{i31}$. In the SQM, we also consider outcomes at the end of round 1, but students have an additional option: they can choose to delay, yielding utility $v_{i21} + \epsilon_{i21}$, which includes an option value (see Equation (4)). Welfare values are assigned based on simulated first-round decisions, using the same set of shocks across both mechanisms.[40]

We highlight two main results from Table 9. First, average welfare changes are positive and large, for all pairs of potential match outcomes. Welfare gains, in distance-equivalent terms, range from 430 kilometers (for students who drop out under both mechanisms) to 1,724 kilometers (for students who drop out under the 1RM but accept an offer in the SQM). Unconditional on the match outcomes, the mean welfare gain is equivalent to a decrease in the distance between student's home location and the program of as much as 861 kilometers.[41] Second, average welfare gains are two to three times larger for students whose match outcomes differ between the SQM and the 1RM, compared to those whose outcomes are the same under both mechanisms. More broadly, the shares of students who delay in round 1 of the SQM—reported by match outcome pairs in Table 9—show that welfare gains tend to be higher in groups where a larger fraction of students choose to delay. This pattern arises because only students who delay at the end of round 1 in the SQM—and who may therefore receive a different final assignment than under the 1RM—experience a change (specifically, an increase) in welfare relative to the 1RM.

As Table 9 reveals that welfare gains are substantial and captured by those choosing to delay in round 1, two natural questions arise: who are the students who do not delay, and why do they not do so? Among students with no top-ranked offer in round 1, as many as 41% choose not to delay.[42] Comparing Column (3) to Column (2) in Table 8 reveals that students are not equally likely to make use of the delaying option. Relative to the average student who does not receive a top-ranked offer in the first round of the SQM, delaying is more prevalent among those who are ineligible for a scholarship, come from high-SES households, are enrolled in an academic track, or belong to the unobserved type 1. These

[40]Specifically, for each set of students $\mathcal{S}$ (with cardinality denoted $|\mathcal{S}|$), welfare differences reported in Table 9 are computed as follows:

$$\frac{1}{|\mathcal{S}|}\sum_{i\in\mathcal{S}}(U_{i1}^{\text{SQM}}-U_{i1}^{\text{1RM}})/(-\phi_6) \quad \text{with} \quad U_{i1}^{\text{1RM}}=\max_{k=1,3}\{v_{ik1}+\tilde{\epsilon}_{ik1}\}, \quad U_{i1}^{\text{SQM}}=\max_{k=1,2,3}\{v_{ik1}+\tilde{\epsilon}_{ik1}\},$$

where $\{\tilde{\epsilon}_{ik1}\}_{k,i}$ are simulation draws from the distribution of the idiosyncratic preference shocks, and where rescaling by the (opposite of the) utility parameter on distance $-\phi_6$ (see Equation (13) and Table C-1) allows to express utility differences in kilometers.

[41]Recall that we are restricting the analysis to students who do not receive an offer from their top-ranked program in round 1. Mean welfare gains are smaller, but still sizable, when considering the full sample of applicants (353 kilometers in distance-equivalent terms).

[42]Students not delaying represent 56% (Table 9) of those with no match in either mechanism (8%, Table 4) and 57% of those with the same match in either mechanism (Table 9), that is, 57% of 64% of the population of applicants without a top-ranked offer (Table 4). Hence, a total share of $.56 \times .08 + .57 \times .64 = .41$.

Table 9: Welfare Effects by Match Outcome

	Sequential Mechanism			
	Drop Out	Accept		Total
One-Round Mechanism				
Drop Out	430	1,724		1,173
Share Delaying in Round 1	*.44*	*1.00*		*.76*
		Same Match	Higher Rank	
Accept	1,397	615	1,479	791
Share Delaying in Round 1	*1.00*	*.43*	*1.00*	*.55*
Total	901	854		861
Share Delaying in Round 1	*.71*	*.56*		*.59*

Notes. This table shows welfare effects of the SQM relative to the 1RM, in kilometers, as a function of match outcomes in each mechanism, that is, as a function of whether they accept an offer or drop out of the platform under under each mechanism.

patterns are directly consistent with the heterogeneity observed in our estimates of both the utility of dropping out and waiting costs (Table C-8). They also reflect differences across students in the option value of waiting, which primarily arise from heterogeneity in students' preferences over programs. While heterogeneity in the option value of delaying could in principle also arise from differences in the probability of receiving a later-round offer, we do not find evidence of this (see Figure D-2 and Table D-3).[43] Overall, these results indicate that heterogeneity in waiting costs and in the outside option utility are key determinants of the decision to delay, and thus of the welfare gains associated with the sequential admission procedure.

8 Concluding Remarks

This paper empirically investigates whether sequential assignment procedures can mitigate inefficiencies caused by off-platform options. We focus on the French higher education market, which provides a valuable setting to study this question, as it features a nationwide centralized system with a three-round sequential mechanism that reallocates offers declined by students who opt for off-platform alternatives. We develop a parsimonious dynamic model of application and acceptance decisions, which captures a key dynamic trade-off between re-

[43]It is also worth nothing that the rank of the offer is similar for all groups (see Table D-2). Intuitively, holding everything else constant, a student with more programs ranked ahead of their first-round offer may have a higher probability of receiving a new offer, simply because more opportunities remain available.

ceiving a potentially better offer in the next round and the cost of delayed certainty about final placement. We estimate this model using detailed administrative data covering the universe of high school applicants—including their applications and decisions across admission rounds and enrollment patterns.

Despite large waiting costs, counterfactual simulations reveal that the three-round sequential mechanism used in France significantly outperforms a more standard one-round alternative in terms of matches, graduation outcomes, and student welfare. These effects are driven by the group of students who do not receive their first-ranked alternative in round 1, and attach a large value to the option of waiting for a better match. In particular, the share of students leaving the higher education system without a degree decreases by 5.4% among students who do not receive an offer from their top-ranked program under the one-round mechanism. Having the option to delay and wait for better offers results in large welfare improvements, with an average gain equivalent to enrolling in a program 353 kilometers closer to home. This increases to 861 kilometers for around 40% of students who actually have an opportunity to delay acceptance, as they are not initially admitted to their top-ranked program.

Taking stock, our analysis provides evidence that multi-round admission mechanisms are an effective way to reduce the inefficiencies induced by the frequent coexistence of a centralized system and off-platform options. From a policy perspective, our findings also point to the importance of combining this type of sequential mechanism with measures to lower waiting costs, such as reducing the duration across admission rounds, and mitigating late-match impacts such as expanding affordable student housing.

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A Institutional Background and Data

A.1 Institutional Background: Additional Details

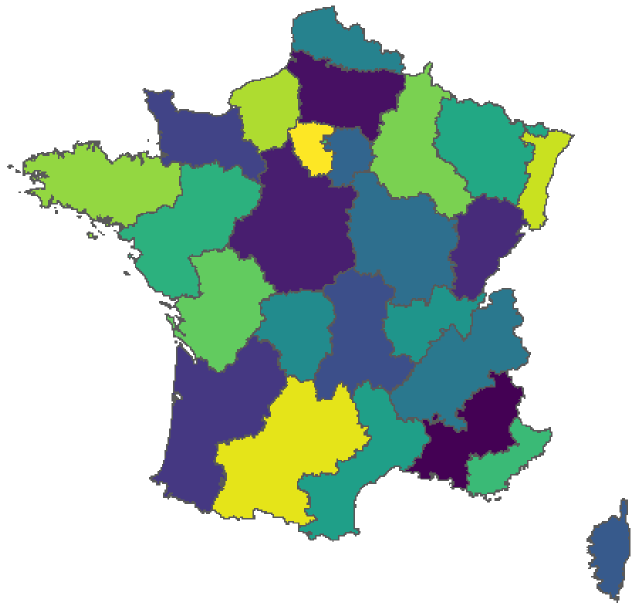
Secondary Education in France. Primary, secondary, and higher education in France are centralized and overseen by the Ministry of Education. The national curriculum is standardized across all schools, and formal tracking does not begin until high school (grades nine through twelve). At that point, students make two key decisions. First, they select one of three *tracks*: *academic*, *technical*, or *vocational*. Second, within their chosen track, they choose a *high school major*, which determines the specific courses they will take. In our empirical analysis, we distinguish four tracks by separating the academic track into two groups: one with a major in sciences and another with a major in humanities or social sciences. At the end of twelfth grade, all students take a national examination—the *Baccalauréat*—whose content depends on their track and major. Passing the Baccalauréat is required to graduate from high school and qualify for entry into higher education. Figure to enter higher education. Figure A-1 displays the geographic regions used by Bachelor programs to define coarse priority groups.

Catchment Areas. The country is partitioned into 30 catchment areas, called *académies* (Figure A-1). Each of them is responsible for implementing and managing educational policies within its region, in accordance with directives from the Ministry of Education.

SES. Following the classification used by the Ministry of Higher Education, we define SES based on the socio-professional category of the student's legal guardian. The data include four categories: High (company managers, executives, liberal professionals, engineers, intellectual and artistic occupations), Medium-High (technicians and associate professionals), Medium-Low (farmers, craft and trades workers, service and sales workers), and Low (manual workers and unemployed individuals). Details on this classification can be found in Merle (2013).

End-of-high-school-exam performance. The end-of-high school exam is graded on a 20-point scale. In our college application data, scores are reported using a four-category classification: highest honors (above 16 out of 20); high honors (14–16); honors (12–14); and pass (10–12). A score of 10 is the minimum required to pass the exam, graduate from high

Figure A-1: Academic regions in France



school, and become eligible for post-secondary education. All students in our sample meet this threshold and are eligible to enter higher education.

A.2 Data: Additional Details on Sample and Variable Construction

Cost of housing and urban location. Measures of local rents for 99 cities in France are taken from: https://www.century21.fr/pdf/logement_etudiant/2015/logement_etudiant_2015.pdf. These 99 cities are referred to as "urban" in the paper.

Off-Platform Programs. We leverage a unique opportunity to track students across the higher education market in France—whether they enroll in programs that participate in the centralized platform or not—using the national census of higher education enrollments (SISE).

This dataset also allows us to estimate the share of students who enroll in off-platform programs. However, the SISE data do not directly indicate whether a program is on- or off-platform, and program identifiers are not aligned with those used in the centralized allocation system (APB). To address this, we adopt the following strategy. First, we complement the SISE data with information on the number of nursing programs and their enrollments as students enrolled in nursing programs are not included in the 2015 SISE dataset. From there, we define a program in SISE as an institution–diploma pair. This gives 8,040 programs in 2015, with a total of 374,964 students enrolled. We then merge the SISE and APB datasets using student identifiers and compute the share of students enrolled in each SISE program who accepted an offer through APB.[44] We classify a SISE program as on-platform if at least one-third of its enrolled students are matched to an APB offer. This threshold accounts for both sample restrictions we made in the APB data (e.g., exclusion of students with missing high school grades) and the possibility that some students may renege on their accepted APB offer at the start of the academic year. As a result, even for on-platform programs, the share of enrolled students with an APB offer may fall below 100%. Using this classification, we estimate that 13.3% of first-year higher education programs in France are off-platform, and they account for 11.8% of total student enrollment. Table A-1 gives an overview of on- and off-platform programs.

[44]Because SISE programs are more aggregated than APB programs, students enrolled in the same SISE program may have accepted offers from different APB programs.

Table A-1: Types of post-secondary programs in France

ON-PLATFORM PROGRAMS	
Bachelor programs	Three-year programs offered by public universities Graduates can enter the labor force or further pursue a Master's degree Deliver the degree of *Licence* (equiv. to Bachelor)
Technical programs	Two-year programs offered by (public) institutes of technology Train mid-level technical workers Graduates can further their education by enrolling in Bachelor programs or engineering- and business-school programs Deliver the degree *Diplôme universitaire de technologie*
Vocational programs	Two-year programs offered by high schools Typically prepare students to enter the labor force, graduates can also further their education by enrolling in Bachelor programs Deliver the degree *Brevet de technicien supérieur*
Prep-school programs	Two-to-three-year programs offered by high schools Prepare students for the competitive exams to enter *Grandes écoles* (highly selective and public and private institutions)
Other programs	Typically offered by private engineering and business schools
OFF-PLATFORM PROGRAMS[1]	
Bachelor programs	(1) Programs offered by public institutions not participating in the centralized process (Paris Dauphine, several political science institutes,...) (2) Double major programs, offered by universities otherwise participating on the platform
Technical programs	Nursing and paramedical degrees (two- and three-year programs, depending on the specific field)
Other programs	24 of the 36 private business schools recruiting after high-school 9 of the 76 private engineering schools recruiting after high-school Art schools

This table defines the main types of post-secondary programs in France. Each individual program is further defined by its *field of study* or *major*, and its host institution. [1]Source: Cour des Comptes (2017)

Table A-2: Sample Description

	Mean
	(1)
Demographics	
Female	0.53
High SES	0.31
Medium-High SES	0.16
Medium-Low SES	0.30
Low SES	0.24
Means-based scholarship recipient	0.17
High-school Track	
Academic	0.61
Technical	0.22
Vocational	0.16
Academic High-school Track - Major	
Sciences	0.54
Social Sciences	0.31
Humanities	0.15
High-School GPA	
Academic Track	0.12
Technical Track	-0.11
Vocational Track	0.35
Applications and Offers	
Number Applications	6.61
Rank Round-One Offer	2.22
Rank Accepted Offer	1.98
Round-one Offer Outside of Rank 1	0.38
No Round-One Offer	0.14
Matched Program	
Bachelor	0.48
Prep-school	0.10
Technical	0.12
Vocational	0.22
Other	0.07
STEM major	0.29
Econ./Law major	0.14
Humanities major	0.19
Production	0.13
Services	0.24
Distance (in 100km)	0.60
Urban	0.64
Monthly rent in 100 EUR (cond. on urban)	4.59
Observations	426,799

Notes. This table describes the characteristics of applicants and their final assignment. Unless otherwise specified, numbers provided are sample shares. GPA was standardized to be mean 0 and standard deviation 1. See Appendix A.2 for details about the definition of socio-economic categories and the construction of average rent and urban dummy.

Table A-3: Probability of Delaying - Current Offer Rank Effects

	Round 1		Round 2	
Rank 3	0.108	(0.004)	0.065	(0.006)
Rank 4	0.173	(0.006)	0.110	(0.008)
Rank 5	0.200	(0.008)	0.124	(0.010)
Rank 6	0.242	(0.010)	0.149	(0.011)
Rank 7	0.262	(0.011)	0.170	(0.013)
Rank 8	0.281	(0.013)	0.169	(0.015)
Rank 9	0.274	(0.015)	0.173	(0.018)
Rank 10 or more	0.308	(0.018)	0.203	(0.021)
Higher-Rank Controls	Yes		Yes	
Top-Rank Controls	Yes		Yes	
Demographics Controls	Yes		Yes	
Nber Students	141,210		73,575	

NOTES. This table shows the increase in the probability to delay acceptance associated with holding an offer from one's j-ranked program relative to holding an offer from the second-ranked program.The regression controls for the type and major of the top-ranked program, the number of programs of each type and major ranked higher than their current offer as well as student's demographic characteristics, including gender and SES status. The sample is restricted to students holding an offer out of their top-ranked program. Standard errors are shown in parenthesis.

Table A-4: Probability of Delaying - Location Effects

	Round 1		Round 2	
	(1)	(2)	(3)	(4)
Region of current alternative/Top-ranked alternative				
Home/Not Home	-0.005	-0.014	-0.029	-0.054
	(0.007)	(0.007)	(0.011)	(0.011)
Not Home/Home	0.085	0.093	0.053	0.040
	(0.008)	(0.008)	(0.012)	(0.012)
Not Home/Not Home (Same)	0.030	0.011	-0.051	-0.042
	(0.006)	(0.006)	(0.009)	(0.010)
Not Home/Not Home (Different)	0.057	0.036	-0.035	-0.066
	(0.006)	(0.006)	(0.009)	(0.009)
Higher-Rank Controls	No	Yes	No	Yes
Top-Rank Controls	No	Yes	No	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Nber Students	51,223	51,223	21,042	21,042

Notes. This table shows the change in the probability to delay associated to the location of the current and potential future offer, relative to when both are located in the student's home region. The sample is restricted to students holding an offer from their second-ranked program. The set of demographic controls include gender and SES status. Columns (2) and (4) also include controls for the current and potential future offer type and major. *Reading: Among students holding an offer from their second-ranked program, those holding an offer located in their home region while their top-ranked program is not have a 1.4 percentage point lower probability to delay in the first round compared to students for whom both current offer and top-ranked programs are located in the student's home region.*

B Parameterization

Recall from Section 4.2 that accepting an offer from program j in Round t yields:

$$v_{i1t} = u_{j_t}(S_i, \tau_i, d_{ij_t}) + w_{j_t}(S_i, \tau_i),$$

where $w_{j_t}(S_i, \tau_i)$ captures the fact that the utility derived from accepting a program at round t may differ from the perceived utility of doing so at the time of submitting the ROL. Here, we present the parameterization used for $w_{j_t}(S_i, \tau_i)$:

$$w_{j_t}(S_i, \tau_i) = z'_{j_t}\pi_{1\tau_i} + z'_{j_t}\Pi_2 x_i + \ell'_{j_t}\pi_{3\tau_i} + \ell'_{j_t}\Pi_4 x_i + \pi_{5\tau_i} c_{ij_t} + x'_i \pi_6 c_{ij_t} \qquad \text{(B-1)}$$

where all elements are defined in Section 5.2.

Graduation index. We parameterize the graduation index of Section 4.3 as follows:

$$h_m(S_i, \tau_i, j_i) = z_m^{G\prime}\psi_{1\tau_i} + z_m^{G\prime}\Psi_2 x_i + z_m^{G\prime}\Psi_3 z_{j_i} \\ + \psi_4 s_{mj_i} + s_{mj_i} r'_{j_i}\psi_5 + z_m^{G\prime}\Psi_6 r_{j_i} + \mathbf{1}[m=0]x'_i\Psi_7 r_{j_i} + \mathbf{1}[m=0]\psi_{8\tau} r_{j_i} \tag{B-2}$$

where z_{j_i} is a vector of dummies corresponding to the type — including Bachelor program, vocational, technical, two-year prep school and other — and major — STEM, Economics/Law, Humanities, Production, Services — of the program j_i the student enrolls in. z_m^G is a vector of dummies corresponding to the type and major of the program the student graduates from. z_m^G includes the same categories as in z_{j_i} with the exception of two-year prep school — while students can enroll in a two-year prep school program after high school, they do not deliver degrees and instead prepare students to take the entry exam of elite engineering and business schools. Hence, z_m^G includes five types of programs one may graduate from —Bachelor program, vocational, technical, elite, and other. s_{mj_i} is a dummy variable equal to one if the program of enrollment j_i is the same as the program of graduation m.[45] The matrix Ψ_3 captures different costs of switching between the type of program of enrollment and graduation, as well as different major switching costs. r_{j_i} is a vector of dummies corresponding to the rank of program j_i in i's ROL.[46] $\mathbf{1}[m=0]$ is a dummy variable equal to one if the student exits the higher education system without earning a degree.

[45] When j_i is a two-year prep school and m is an elite program, $s_{mj_i} = 1$.

[46] We include dummies for rank 2, 3, 4, and "5 or above". Rank 1 is used as the baseline.

C Model Estimates

C.1 Preferences for programs, waiting costs, utility from dropping out of the platform

Table C-1: Program Utility - Common Component

	Coeff. (1)	St. Error (2)
Program type (Benchmark = Bachelor)		
Prep-School	-0.007	(0.129)
Technical	1.302	(0.133)
Vocational	-1.614	(0.157)
Other	0.599	(0.133)
Program major (Benchmark = STEM)		
Economics-Law	0.420	(0.130)
Humanities	1.663	(0.119)
Services	-1.002	(0.100)
Location		
Distance	-1.040	(0.020)
Same Catchment Area	1.770	(0.029)
Paris	0.275	(0.062)
Urban	-0.293	(0.088)
Urban × Same Catchment Area	0.782	(0.106)
Rent	0.179	(0.018)
Rent × Same Catchment Area	-0.220	(0.022)

Notes. Estimates of Equation (13) up to scale, i.e. ϕ/σ and Φ/σ. Distance in km is divided by 100. Rent in monthly EUR is divided by 100. Bootstrap standard errors in parentheses.

Figure C-1: Distribution of Waiting Costs at the End of Round 2

Notes. This figure shows the distribution of estimated waiting costs for students who have the possibility to *delay* in round 2, i.e. those with an offer outside of their top-ranked program at the end of round 1. Waiting costs are expressed in distance-increase-equivalent (in km).

Table C-2: Program Utility - Heterogeneity (Part 1 of 3)

	Coeff. (1)	St. Error (2)
Panel A: SES Group (Benchmark = High SES)		
Program Type		
Medium-High × Prep-School	-0.314	(0.091)
Medium-High × Technical	0.017	(0.134)
Medium-High × Vocational	0.030	(0.123)
Medium-High × Other	-0.170	(0.148)
Medium-Low × Prep-School	-0.595	(0.108)
Medium-Low × Technical	-0.362	(0.108)
Medium-Low × Vocational	-0.253	(0.113)
Medium-Low × Other	-0.757	(0.123)
Low × Prep-School	-0.603	(0.157)
Low × Technical	-0.570	(0.114)
Low × Vocational	-0.242	(0.118)
Low × Other	-0.724	(0.121)
Program Major		
Medium-High × Economics-Law	-0.562	(0.120)
Medium-High × Humanities	0.011	(0.111)
Medium-High × Services	-0.235	(0.106)
Medium-Low × Economics-Law	-0.475	(0.124)
Medium-Low × Humanities	-0.221	(0.107)
Medium-Low × Services	0.242	(0.107)
Low × Economics-Law	-0.491	(0.126)
Low × Humanities	-0.208	(0.133)
Low × Services	0.301	(0.106)
Panel B: Scholarship Status (Benchmark = Without Scholarship)		
Program Type		
With Scholarship × Prep-School	-0.174	(0.144)
With Scholarship × Technical	-0.246	(0.110)
With Scholarship × Vocational	-0.423	(0.120)
With Scholarship × Other	-0.182	(0.118)
Program Major		
With Scholarship × Economics-Law	-0.017	(0.152)
With Scholarship × Humanities	-0.185	(0.111)
With Scholarship × Services	0.133	(0.076)

Notes. Estimates of Equation (13) up to scale, i.e. ϕ/σ and Φ/σ. Bootstrap standard errors in parentheses.

Table C-3: Program Utility - Heterogeneity (Part 2 of 3)

	Coeff. (1)	St. Error (2)
Panel A: High School Track (Benchmark = Academic - Humanities & Social Sciences)		
Program Type		
Academic Track - Sciences × Prep-School	0.492	(0.121)
Academic Track - Sciences × Technical	-0.093	(0.127)
Academic Track - Sciences × Vocational	-0.295	(0.162)
Academic Track - Sciences × Other	1.007	(0.132)
Technological Track × Prep-School	-0.961	(0.164)
Technological Track × Technical	0.342	(0.132)
Technological Track × Vocational	1.983	(0.136)
Technological Track - Sciences × Other	0.277	(0.135)
Vocational Track × Prep-School	-0.961	(0.164)
Vocational Track × Technical	-0.047	(0.211)
Vocational Track × Vocational	3.770	(0.183)
Vocational Track - Sciences × Other	1.024	(0.176)
Program Major		
Academic Track - Sciences × Economics-Law	-4.479	(0.132)
Academic Track - Sciences × Humanities	-3.871	(0.120)
Academic Track - Sciences × Services	-4.355	(0.103)
Technological Track × Economics-Law	-2.395	(0.148)
Technological Track × Humanities	-2.820	(0.117)
Technological Track × Services	-1.438	(0.094)
Vocational Track × Economics-Law	-2.395	(0.148)
Vocational Track × Humanities	-1.728	(0.150)
Vocational Track × Services	-1.740	(0.130)
Panel B: Gender (Benchmark = Male)		
Program Type		
Female × Prep-School	-0.727	(0.082)
Female × Technical	-1.495	(0.096)
Female × Vocational	-1.347	(0.086)
Female × Other	-0.981	(0.088)
Program Major		
Female × Economics-Law	0.511	(0.078)
Female × Humanities	0.976	(0.074)
Female × Services	1.899	(0.070)

Notes. Estimates of Equation (13) up to scale, i.e. ϕ/σ and Φ/σ. Bootstrap standard errors in parentheses.

Table C-4: Program Utility - Heterogeneity (Part 3 of 3)

	Coeff. (1)	St. Error (2)
Panel A: GPA (Benchmark = Academic Track - Humanities & Social Sciences)		
Program Type		
GPA × Prep-School	1.610	(0.086)
GPA × Technical	0.915	(0.103)
GPA × Vocational	0.448	(0.107)
GPA × Other	0.721	(0.116)
Academic Track - Sciences × GPA × Prep-School	-0.214	(0.116)
Academic Track - Sciences × GPA × Technical	-1.093	(0.124)
Academic Track - Sciences × GPA × Vocational	-0.952	(0.130)
Academic Track - Sciences × GPA × Other	-0.158	(0.128)
Technological Track × GPA × Prep-School	-0.461	(0.164)
Technological Track × GPA × Technical	-0.512	(0.124)
Technological Track × GPA × Vocational	-0.423	(0.110)
Technological Track × GPA × Other	-0.199	(0.163)
Vocational Track × GPA × Prep-School	-0.461	(0.164)
Vocational Track × GPA × Technical	0.163	(0.220)
Vocational Track × GPA × Vocational	0.488	(0.198)
Vocational Track × GPA × Other	0.316	(0.239)
Program Major		
GPA × Economics-Law	0.420	(0.130)
GPA × Humanities	0.788	(0.094)
GPA × Services	-1.002	(0.100)
Academic Track - Sciences GPA × Economics-Law	-0.751	(0.111)
Academic Track - Sciences GPA × Humanities	-0.995	(0.128)
Academic Track - Sciences GPA × Services	-0.323	(0.113)
Technological Track × Economics-Law	-0.846	(0.149)
Technological Track × Humanities	-0.884	(0.134)
Technological Track × Services	0.159	(0.116)
Vocational Track × GPA × Economics-Law	-0.846	(0.149)
Vocational Track × GPA × Humanities	-0.537	(0.172)
Vocational Track × GPA × Services	0.140	(0.130)
Panel B: Unobserved Type (Benchmark = Type 1)		
Program Type		
Type 2 × Prep-School	-2.017	(0.084)
Type 2 × Technical	-2.110	(0.077)
Type 2 × Vocational	-2.090	(0.075)
Type 2 × Other	-3.276	(0.082)
Program Major		
Type 2 × Economics-Law	3.871	(0.088)
Type 2 × Humanities	-0.610	(0.077)
Type 2 × Services	5.507	(0.074)

Notes. Estimates of Equation (13) up to scale, i.e. ϕ/σ and Φ/σ. Bootstrap standard errors in parentheses.

Table C-5: Utility from Accepting (Part 1 of 3)

	Round 1 (1)		Round 2 (2)		Round 3 (3)	
Program Type (Benchmark = Bachelor)						
Prep-School	2.382	(0.312)	2.346	(0.376)	1.794	(0.426)
× Medium-High SES	0.276	(0.203)	0.180	(0.233)	0.063	(0.370)
× Medium-Low SES	-0.128	(0.200)	0.063	(0.240)	-0.247	(0.374)
× Low SES	-0.029	(0.255)	0.083	(0.272)	-0.308	(0.491)
× With Scholarship	-0.005	(0.315)	-0.483	(0.299)	0.521	(2.072)
× Female	0.091	(0.145)	0.088	(0.174)	-0.094	(0.228)
× Type 2	-0.510	(0.175)	-0.590	(0.208)	-0.730	(0.229)
× Gen. Track - Sc.	-0.923	(0.363)	-1.075	(0.456)	-0.105	(0.449)
× Tech. Track	0.295	(0.269)	0.445	(0.562)	0.361	(3.127)
× Voc. Track	0.295	(0.269)	0.445	(0.568)	0.361	(3.234)
× GPA	-0.915	(0.213)	-0.683	(0.250)	-0.653	(0.284)
× GPA × Gen.-Sc.	0.784	(0.242)	0.992	(0.290)	0.411	(0.328)
× GPA × Tech. Track	0.701	(0.253)	-0.173	(0.582)	0.280	(1.184)
× GPA × Voc. Track	0.701	(0.253)	-0.173	(0.612)	0.280	(1.235)
Technical	1.013	(0.228)	0.105	(0.471)	1.087	(0.554)
× Medium-High SES	0.390	(0.251)	0.493	(0.289)	0.366	(0.408)
× Medium-Low SES	0.054	(0.169)	0.097	(0.217)	0.289	(0.293)
× Low SES	0.353	(0.202)	0.346	(0.306)	0.000	(0.359)
× With Scholarship	-0.036	(0.206)	-0.274	(0.294)	-0.338	(0.382)
× Female	0.488	(0.182)	0.731	(0.193)	0.462	(0.285)
× Type 2	-0.023	(0.157)	-0.017	(0.215)	0.369	(0.416)
× Gen. Track - Sc.	-0.531	(0.195)	0.152	(0.421)	-0.330	(0.531)
× Tech. Track	0.829	(0.251)	0.833	(0.468)	1.077	(0.685)
× Voc. Track	0.016	(0.769)	-0.534	(0.888)	0.395	(5.197)
× GPA	-0.713	(0.264)	-0.946	(0.526)	-1.071	(0.674)
× GPA × Gen.-Sc.	0.032	(0.244)	0.473	(0.567)	0.815	(0.781)
× GPA × Tech. Track	0.496	(0.343)	0.879	(0.584)	1.204	(1.038)
× GPA × Voc. Track	1.329	(0.681)	0.860	(0.906)	0.273	(4.998)
Vocational	0.771	(0.214)	0.465	(0.416)	1.016	(0.584)
× Medium-High SES	0.222	(0.178)	0.039	(0.247)	0.233	(0.263)
× Medium-Low SES	-0.052	(0.147)	-0.039	(0.228)	0.354	(0.302)
× Low SES	-0.030	(0.139)	-0.163	(0.198)	0.053	(0.311)
× With Scholarship	-0.125	(0.190)	-0.205	(0.218)	-0.446	(0.340)
× Female	0.508	(0.162)	0.256	(0.193)	0.409	(0.267)
× Type 2	0.111	(0.151)	-0.140	(0.234)	-0.061	(0.354)
× Gen. Track - Sc.	-0.550	(0.188)	0.446	(0.500)	0.486	(0.618)
× Tech. Track	0.594	(0.210)	0.702	(0.441)	0.794	(0.676)
× Voc. Track	-0.078	(0.206)	0.266	(0.505)	-0.021	(0.672)
× GPA	-0.628	(0.268)	-0.994	(0.502)	-0.050	(0.590)
× GPA × Gen.-Sc.	0.079	(0.255)	0.930	(0.537)	0.346	(0.716)
× GPA × Tech. Track	0.544	(0.306)	0.835	(0.513)	0.502	(0.667)
× GPA × Voc. Track	0.517	(0.316)	0.579	(0.473)	-0.009	(0.710)
Other	1.220	(0.241)	0.523	(0.329)	1.136	(0.499)
× Medium-High SES	-0.006	(0.232)	0.193	(0.302)	0.090	(0.475)
× Medium-Low SES	-0.213	(0.209)	0.180	(0.282)	0.230	(0.405)
× Low SES	-0.134	(0.188)	-0.144	(0.310)	-0.263	(0.510)
× With Scholarship	-0.234	(0.292)	0.258	(0.384)	-1.127	(0.571)
× Female	0.420	(0.166)	0.289	(0.247)	0.153	(0.370)
× Type 2	-0.441	(0.215)	-0.374	(0.301)	-0.364	(0.452)
× Gen. Track - Sc.	-0.501	(0.210)	-0.181	(0.333)	0.044	(0.497)
× Tech. Track	0.505	(0.257)	0.368	(0.369)	0.683	(0.591)
× Voc. Track	0.204	(0.291)	-0.706	(0.760)	0.096	(0.822)
× GPA	-0.667	(0.226)	-0.928	(0.386)	-0.090	(0.567)
× GPA × Gen.-Sc.	0.351	(0.260)	0.769	(0.398)	-0.060	(0.586)
× GPA × Tech. Track	0.498	(0.266)	0.032	(0.426)	0.211	(0.610)
× GPA × Voc. Track	0.135	(0.398)	1.372	(0.650)	0.556	(1.090)

NOTES. Estimates of Equation (B-1). Bootstrap standard errors in parentheses.

Table C-6: Utility from Accepting (Part 2 of 3)

	Round 1		Round 2		Round 3	
	(1)		(2)		(3)	
Program Major (Benchmark = STEM)						
Economics-Law	-0.447	(0.167)	-1.234	(0.227)	-0.578	(0.218)
× Medium-High SES	0.292	(0.138)	0.045	(0.218)	0.006	(0.226)
× Medium-Low SES	0.272	(0.114)	0.084	(0.195)	0.123	(0.201)
× Low SES	0.448	(0.134)	0.227	(0.217)	-0.033	(0.215)
× With Scholarship	0.111	(0.118)	0.068	(0.187)	0.288	(0.255)
× Female	0.449	(0.089)	0.602	(0.162)	0.466	(0.169)
× Type 2	0.001	(0.150)	-0.096	(0.194)	0.344	(0.196)
× Gen. Track - Sc.	-0.238	(0.160)	0.318	(0.205)	-0.304	(0.197)
× Tech. Track	0.053	(0.136)	0.831	(0.268)	0.397	(0.267)
× Voc. Track	-0.041	(0.250)	0.800	(0.335)	0.379	(0.403)
× GPA	-0.188	(0.109)	-0.239	(0.188)	-0.207	(0.180)
× GPA × Gen.-Sc.	-0.120	(0.147)	0.027	(0.198)	-0.072	(0.207)
× GPA × Tech. Track	0.327	(0.142)	0.721	(0.297)	0.689	(0.294)
× GPA × Voc. Track	0.106	(0.203)	-0.035	(0.385)	0.354	(0.544)
Humanities	-0.333	(0.133)	-1.184	(0.169)	0.048	(0.181)
× Medium-High SES	0.186	(0.131)	0.090	(0.202)	-0.178	(0.221)
× Medium-Low SES	0.210	(0.101)	0.209	(0.168)	0.013	(0.187)
× Low SES	0.409	(0.107)	0.344	(0.168)	0.101	(0.250)
× With Scholarship	-0.168	(0.092)	-0.313	(0.183)	-0.074	(0.221)
× Female	0.104	(0.084)	0.536	(0.121)	0.221	(0.168)
× Type 2	0.027	(0.079)	-0.099	(0.133)	0.122	(0.153)
× Gen. Track - Sc.	-0.460	(0.132)	0.095	(0.199)	-0.448	(0.214)
× Tech. Track	0.211	(0.132)	0.680	(0.226)	0.377	(0.218)
× Voc. Track	0.126	(0.197)	0.904	(0.323)	0.074	(0.397)
× GPA	-0.105	(0.099)	-0.153	(0.157)	-0.342	(0.188)
× GPA × Gen.-Sc.	-0.211	(0.133)	-0.487	(0.224)	-0.399	(0.258)
× GPA × Tech. Track	-0.036	(0.163)	0.223	(0.208)	0.603	(0.311)
× GPA × Voc. Track	-0.045	(0.204)	-0.322	(0.334)	-0.427	(0.387)
Services	-0.485	(0.222)	-0.655	(0.430)	-0.088	(0.538)
× Medium-High SES	0.001	(0.170)	0.165	(0.239)	-0.474	(0.300)
× Medium-Low SES	0.131	(0.146)	0.208	(0.244)	-0.443	(0.228)
× Low SES	0.037	(0.158)	0.325	(0.221)	-0.244	(0.299)
× With Scholarship	0.206	(0.182)	0.267	(0.222)	0.633	(0.304)
× Female	-0.425	(0.149)	-0.278	(0.190)	-0.229	(0.251)
× Type 2	0.162	(0.184)	0.368	(0.229)	-0.082	(0.418)
× Gen. Track - Sc.	0.119	(0.231)	-0.213	(0.492)	-0.436	(0.567)
× Tech. Track	0.008	(0.219)	-0.050	(0.414)	-0.140	(0.637)
× Voc. Track	0.686	(0.226)	0.358	(0.440)	0.397	(0.620)
× GPA	0.296	(0.229)	0.338	(0.467)	-0.006	(0.602)
× GPA × Gen.-Sc.	0.042	(0.223)	-0.322	(0.552)	-0.280	(0.636)
× GPA × Tech. Track	-0.208	(0.245)	-0.003	(0.524)	-0.045	(0.619)
× GPA × Voc. Track	-0.511	(0.263)	-0.509	(0.481)	-0.087	(0.691)

Notes. Estimates of Equation (B-1). Bootstrap standard errors in parentheses.

Table C-7: Utility from Accepting (Part 3 of 3)

	Round 1		Round 2		Round 3	
	(1)		(2)		(3)	
Same Catchment Area	-0.085	(0.067)	-0.337	(0.127)	-0.032	(0.153)
× Medium-High SES	0.054	(0.065)	0.054	(0.135)	0.170	(0.177)
× Medium-Low SES	0.038	(0.065)	-0.071	(0.115)	0.165	(0.119)
× Low SES	0.060	(0.068)	0.011	(0.127)	0.325	(0.176)
× With Scholarship	-0.046	(0.065)	0.066	(0.131)	-0.330	(0.136)
× Female	-0.088	(0.053)	-0.135	(0.084)	-0.053	(0.126)
× Type 2	-0.074	(0.048)	0.013	(0.091)	-0.151	(0.111)
× Gen. Track - Sc.	0.127	(0.059)	-0.413	(0.102)	0.085	(0.168)
× Tech. Track	0.109	(0.069)	0.096	(0.134)	-0.017	(0.174)
× Voc. Track	0.466	(0.134)	0.159	(0.170)	0.113	(0.204)
× GPA	-0.036	(0.056)	0.061	(0.084)	0.005	(0.127)
× GPA × Gen.-Sc.	-0.051	(0.063)	-0.132	(0.102)	-0.112	(0.153)
× GPA × Tech. Track	-0.025	(0.084)	-0.110	(0.134)	-0.294	(0.194)
× GPA × Voc. Track	-0.225	(0.121)	-0.001	(0.204)	-0.263	(0.284)
Urban	0.386	(0.215)	0.491	(0.511)	-0.161	(0.573)
× Medium-High SES	-0.306	(0.260)	0.518	(0.427)	-0.041	(0.531)
× Medium-Low SES	-0.124	(0.218)	-0.355	(0.405)	-0.938	(0.601)
× Low SES	-0.567	(0.265)	-0.512	(0.478)	-1.401	(0.599)
× With Scholarship	-0.048	(0.271)	0.134	(0.476)	0.620	(0.603)
× Female	-0.109	(0.159)	0.160	(0.339)	0.188	(0.487)
× Type 2	0.199	(0.163)	-0.257	(0.417)	-0.376	(0.503)
× Gen. Track - Sc.	-0.193	(0.199)	-0.403	(0.422)	0.973	(0.539)
× Tech. Track	-0.506	(0.263)	-0.528	(0.588)	0.577	(0.590)
× Voc. Track	0.169	(0.318)	-0.661	(0.890)	-0.194	(0.919)
× GPA	0.414	(0.162)	0.543	(0.367)	0.232	(0.491)
× GPA × Gen.-Sc.	-0.310	(0.229)	-0.664	(0.544)	0.112	(0.697)
× GPA × Tech. Track	-0.138	(0.240)	0.072	(0.599)	-0.070	(0.894)
× GPA × Voc. Track	-0.927	(0.324)	-0.808	(0.789)	-0.033	(1.207)
Paris	0.616	(0.199)	0.729	(0.391)	-0.106	(0.415)
× Medium-High SES	-0.305	(0.217)	0.535	(0.357)	0.652	(0.470)
× Medium-Low SES	0.094	(0.188)	-0.203	(0.329)	-0.027	(0.498)
× Low SES	-0.449	(0.238)	-0.501	(0.441)	0.017	(0.466)
× With Scholarship	-0.038	(0.213)	-0.096	(0.398)	0.862	(0.551)
× Female	-0.025	(0.134)	-0.075	(0.330)	0.352	(0.364)
× Type 2	0.079	(0.159)	0.165	(0.335)	-0.339	(0.427)
× Gen. Track - Sc.	-0.380	(0.202)	-1.072	(0.348)	0.321	(0.452)
× Tech. Track	-0.440	(0.265)	-0.346	(0.508)	-0.257	(0.670)
× Voc. Track	0.758	(0.325)	-0.867	(0.816)	-1.195	(0.704)
× GPA	0.033	(0.118)	0.194	(0.276)	-0.260	(0.319)
× GPA × Gen.-Sc.	-0.081	(0.158)	-0.509	(0.394)	-0.037	(0.480)
× GPA × Tech. Track	0.263	(0.219)	-0.031	(0.468)	0.276	(0.604)
× GPA × Voc. Track	-0.709	(0.307)	-0.705	(0.771)	0.009	(0.976)
Rent	-0.100	(0.050)	-0.129	(0.114)	0.071	(0.123)
× Medium-High SES	0.095	(0.061)	-0.077	(0.103)	0.053	(0.107)
× Medium-Low SES	0.020	(0.051)	0.119	(0.089)	0.235	(0.131)
× Low SES	0.139	(0.064)	0.154	(0.118)	0.303	(0.132)
× With Scholarship	0.025	(0.059)	-0.042	(0.110)	-0.165	(0.138)
× Female	0.029	(0.036)	-0.038	(0.087)	-0.071	(0.107)
× Type 2	-0.034	(0.039)	0.055	(0.099)	0.068	(0.112)
× Gen. Track - Sc.	0.055	(0.049)	0.060	(0.099)	-0.251	(0.132)
× Tech. Track	0.106	(0.061)	0.095	(0.133)	-0.119	(0.137)
× Voc. Track	-0.064	(0.074)	0.207	(0.217)	0.107	(0.203)
× GPA	-0.075	(0.037)	-0.115	(0.081)	0.000	(0.103)
× GPA × Gen.-Sc.	0.062	(0.051)	0.173	(0.123)	-0.069	(0.159)
× GPA × Tech. Track	0.020	(0.059)	-0.004	(0.130)	-0.006	(0.185)
× GPA × Voc. Track	0.200	(0.078)	0.164	(0.180)	-0.057	(0.271)

NOTES. Estimates of Equation (B-1). Bootstrap standard errors in parentheses.

Table C-8: Utility from Waiting & Drop Out and Additional Results

	Coeff. (1)	St. Error (2)
Panel A: Common Component		
Wait	-0.126	(0.057)
Drop Out × Round 1	-1.808	(0.118)
Drop Out × Round 2	-1.867	(0.120)
Drop Out × Round 3	-0.727	(0.132)
Panel B: Heterogeneity		
SES Group (Benchmark = High-SES)		
Medium-High × Wait	0.103	(0.046)
Medium-Low × Wait	0.062	(0.033)
Low × Wait	0.044	(0.039)
Medium-High × Drop out	-0.084	(0.112)
Medium-Low × Drop out	-0.118	(0.086)
Low × Drop out	-0.153	(0.076)
Scholarship Status (Benchmark = Without Scholarship)		
With Scholarship × Wait	-0.065	(0.036)
With Scholarship × Drop out	-0.460	(0.096)
Gender (Benchmark = Male)		
Female × Wait	-0.007	(0.029)
Female × Drop out	0.370	(0.078)
High School Program (Benchmark = Academic Track - Humanities & Social Sciences)		
Academic Track - Sciences × Wait	0.093	(0.039)
Academic Track - Sciences × Drop out	-0.636	(0.108)
Technological Track × Wait	-0.208	(0.034)
Technological Track × Drop out	0.599	(0.122)
Vocational Track × Wait	-0.465	(0.056)
Vocational Track × Drop out	0.599	(0.122)
GPA (Benchmark = Academic Track - Humanities & Social Sciences)		
GPA × Wait	0.182	(0.030)
GPA × Drop out	-0.250	(0.109)
Academic Track - Sciences × GPA × Wait	0.091	(0.044)
Academic Track - Sciences × GPA × Drop out	-0.176	(0.120)
Technological Track × GPA × Wait	-0.010	(0.054)
Technological Track × GPA × Drop out	0.134	(0.141)
Vocational Track × GPA × Wait	-0.013	(0.055)
Vocational Track × GPA × Drop out	-0.204	(0.186)
Unobserved Heterogeneity (Benchmark = Type 1)		
Type 2 × Wait	0.004	(0.028)
Type 2 × Drop out	0.137	(0.081)
Panel C: Additional Results		
Scale Parameter (σ)	0.098	(0.012)
Share Type 2 (π_2)	0.532	

Notes. Panel A and B contain the estimates of Equation (14) and Equation (15). σ can be found in Equation (7) and π_2 in Equation (16). Bootstrap standard errors in parentheses.

C.2 Graduation Probability

Table C-9: Probability to Graduate (Part 1)

	Coeff. (1)	St. Error (2)
Panel A: Common Component		
Program Type (Benchmark = Drop Out)		
Bachelor	-1.464	(0.073)
Elite	-1.616	(0.092)
Technical	-2.809	(0.127)
Vocational	-1.955	(0.140)
Other	-2.003	(0.088)
Program Major (Benchmark = STEM)		
Economics-Law	0.391	(0.057)
Humanities	0.380	(0.064)
Services	-0.328	(0.129)
Panel B: Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High × Bachelor	0.173	(0.044)
Medium-High × Elite	-0.368	(0.060)
Medium-High × Technical	0.001	(0.082)
Medium-High × Vocational	0.101	(0.073)
Medium-High × Other	0.081	(0.058)
Medium-Low × Bachelor	-0.041	(0.032)
Medium-Low × Elite	-0.597	(0.047)
Medium-Low × Technical	-0.170	(0.076)
Medium-Low × Vocational	-0.081	(0.073)
Medium-Low × Other	-0.207	(0.049)
Low × Bachelor	-0.094	(0.043)
Low × Elite	-0.913	(0.060)
Low × Technical	-0.274	(0.073)
Low × Vocational	-0.051	(0.073)
Low × Other	-0.347	(0.063)
Medium-High × Economics-Law	-0.380	(0.049)
Medium-High × Humanities	-0.119	(0.049)
Medium-High × Services	-0.140	(0.071)
Medium-Low × Economics-Law	-0.203	(0.043)
Medium-Low × Humanities	-0.031	(0.042)
Medium-Low × Services	-0.010	(0.069)
Low × Economics-Law	-0.258	(0.046)
Low × Humanities	-0.085	(0.057)
Low × Services	0.040	(0.064)

NOTES. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

Table C-10: Probability to Graduate (Part 2)

	Coeff. (1)	St. Error (2)
High School Program		
(Benchmark = Academic Track - Humanities & Soc. Sci.)		
Academic Track - Sciences		
× Bachelor	1.204	(0.045)
× Prep-School	1.564	(0.061)
× Technical	1.255	(0.113)
× Vocational	0.521	(0.127)
× Other	1.679	(0.064)
× Economics-Law	-1.637	(0.049)
× Humanities	-1.666	(0.060)
× Services	-1.370	(0.120)
Technological Track		
× Bachelor	-0.409	(0.053)
× Prep-School	-1.190	(0.076)
× Technical	-0.656	(0.110)
× Vocational	-0.018	(0.134)
× Other	0.628	(0.071)
× Economics-Law	-1.024	(0.057)
× Humanities	-1.172	(0.061)
× Services	-0.293	(0.121)
Vocational Track		
× Bachelor	-1.831	(0.070)
× Prep-School	-1.190	(0.076)
× Technical	-2.172	(0.217)
× Vocational	-0.413	(0.135)
× Other	-1.203	(0.106)
× Economics-Law	-1.024	(0.057)
× Humanities	-1.328	(0.114)
× Services	-0.633	(0.134)

NOTES. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

Table C-11: Probability to Graduate (Part 3)

	Coeff. (1)	St. Error (2)
GPA (Benchmark = Academic Track - Humanities & Social Sciences)		
GPA		
× Bachelor	0.619	(0.045)
× Prep-School	0.750	(0.052)
× Technical	0.926	(0.083)
× Vocational	0.791	(0.096)
× Other	0.086	(0.053)
× Economics-Law	0.391	(0.057)
× Humanities	0.063	(0.041)
× Services	-0.328	(0.129)
Academic Track - Sciences		
× GPA × Bachelor	-0.052	(0.048)
× GPA × Prep-School	0.036	(0.055)
× GPA × Technical	-0.340	(0.084)
× GPA × Vocational	-0.629	(0.107)
× GPA × Other	0.397	(0.058)
× Economics-Law	-0.540	(0.047)
× Humanities	-0.514	(0.046)
× Services	0.170	(0.106)
Technological Track		
× GPA × Bachelor	-0.127	(0.064)
× GPA × Prep-School	0.081	(0.083)
× GPA × Technical	-0.288	(0.116)
× GPA × Vocational	-0.711	(0.103)
× GPA × Other	0.426	(0.074)
× Economics-Law	-0.413	(0.064)
× Humanities	-0.051	(0.058)
× Services	0.439	(0.100)
Vocational Track		
× GPA × Bachelor	0.218	(0.086)
× GPA × Prep-School	0.081	(0.083)
× GPA × Technical	0.204	(0.172)
× GPA × Vocational	-0.456	(0.104)
× GPA × Other	0.573	(0.117)
× GPA × Economics-Law	-0.413	(0.064)
× GPA × Humanities	-0.195	(0.124)
× GPA × Services	0.499	(0.111)

Notes. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

Table C-12: Probability to Graduate (Part 4)

	Coeff. (1)	St. Error (2)
Panel A: Scholarship Status (Benchmark = Without Scholarship)		
Program Type		
With Scholarship × Bachelor	-0.271	(0.039)
With Scholarship × Elite	-0.487	(0.065)
With Scholarship × Technical	-0.289	(0.101)
With Scholarship × Vocational	-0.188	(0.077)
With Scholarship × Other	-0.455	(0.054)
Program Major		
With Scholarship × Economics-Law	0.160	(0.042)
With Scholarship × Humanities	0.268	(0.057)
With Scholarship × Services	0.147	(0.091)
Panel B: Gender (Benchmark = Male)		
Program Type		
Female × Bachelor	-0.110	(0.037)
Female × Elite	-0.564	(0.040)
Female × Technical	-0.716	(0.074)
Female × Vocational	-0.388	(0.057)
Female × Other	0.223	(0.042)
Program Major		
Female × Economics-Law	0.238	(0.032)
Female × Humanities	0.477	(0.031)
Female × Services	0.546	(0.063)
Panel C: Unobserved Type (Benchmark = Type 1)		
Program Type		
Type 2 × Bachelor	-0.681	(0.031)
Type 2 × Elite	-0.333	(0.043)
Type 2 × Technical	-1.469	(0.087)
Type 2 × Vocational	-1.677	(0.078)
Type 2 × Other	-0.921	(0.039)
Program Major		
Type 2 × Economics-Law	1.465	(0.043)
Type 2 × Humanities	0.482	(0.038)
Type 2 × Services	2.532	(0.091)

Notes. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

Table C-13: Probability to Graduate (Part 5)

	Coeff. (1)	St. Error (2)
Panel A: Same Type-Major as Enrollment		
Same as Enrollment	0.835	(0.033)
Same as Enrollment × Rank 2	-0.105	(0.043)
Same as Enrollment × Rank 3	-0.229	(0.046)
Same as Enrollment × Rank 4	-0.293	(0.071)
Same as Enrollment × Rank 5 or more	-0.258	(0.052)
Panel B: Enrolled Bachelor		
× Graduate Bachelor	-0.672	(0.051)
× Graduate Elite	-2.129	(0.056)
× Graduate Tech	-1.205	(0.107)
× Graduate Voc	-2.491	(0.107)
× Graduate Other	-2.081	(0.060)
Panel C: Enrolled Prep-School		
× Graduate Bachelor	-0.666	(0.067)
× Graduate Elite	-0.553	(0.081)
× Graduate Tech/Voc	-1.569	(0.124)
× Graduate Other	-1.280	(0.098)
Panel D: Enrolled Technical		
× Graduate Bachelor	0.884	(0.058)
× Graduate Elite	0.025	(0.064)
× Graduate Tech	0.582	(0.096)
× Graduate Voc	-2.971	(0.161)
× Graduate Other	-2.495	(0.101)
Panel E: Enrolled Vocational		
× Graduate Bachelor	0.297	(0.054)
× Graduate Elite	-1.219	(0.076)
× Graduate Tech	-2.980	(0.173)
× Graduate Voc	-0.351	(0.074)
× Graduate Other	-2.624	(0.095)
Panel F: Enrolled Other		
× Graduate Bachelor	-1.041	(0.074)
× Graduate Elite	0.227	(0.068)
× Graduate Tech	-0.812	(0.142)
× Graduate Voc	-0.096	(0.103)
× Graduate Other	-0.898	(0.085)
Panel G: Major Switches		
STEM to STEM	1.334	(0.038)
Econ-Law to Econ-Law	1.110	(0.050)
Humanities to Humanities	1.316	(0.043)
Services to services	1.723	(0.084)
Production to production	2.154	(0.102)
Production to sciences	1.474	(0.056)
Services to Econ-Law	0.713	(0.039)

Notes. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

Table C-14: Probability to Graduate (Part 6)

	Coeff. (1)	St. Error (2)
Panel A: Program Type (Benchmark = Drop Out)		
Bachelor		
× Rank 2	-0.151	(0.105)
× Rank 3	-0.313	(0.152)
× Rank 4	-0.327	(0.158)
× Rank 5 or more	-0.200	(0.121)
Elite		
× Rank 2	-0.031	(0.111)
× Rank 3	-0.033	(0.160)
× Rank 4	0.051	(0.164)
× Rank 5 or more	0.379	(0.131)
Technical		
× Rank 2	0.216	(0.124)
× Rank 3	0.431	(0.180)
× Rank 4	0.060	(0.236)
× Rank 5 or more	0.374	(0.152)
Vocational		
× Rank 2	0.126	(0.114)
× Rank 3	0.303	(0.171)
× Rank 4	0.013	(0.223)
× Rank 5 or more	0.406	(0.140)
Other		
× Rank 2	-0.055	(0.116)
× Rank 3	-0.117	(0.170)
× Rank 4	-0.129	(0.184)
× Rank 5 or more	0.033	(0.135)
Panel B: Program Major (Benchmark = STEM)		
Economics-Law		
× Rank 2	0.207	(0.065)
× Rank 3	0.370	(0.090)
× Rank 4	0.309	(0.100)
× Rank 5 or more	0.415	(0.066)
Humanities		
× Rank 2	0.025	(0.069)
× Rank 3	0.236	(0.076)
× Rank 4	0.054	(0.116)
× Rank 5 or more	0.019	(0.068)
Services		
× Rank 2	-0.105	(0.086)
× Rank 3	-0.039	(0.121)
× Rank 4	0.102	(0.162)
× Rank 5 or more	0.055	(0.110)

NOTES. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

Table C-15: Probability to Graduate (Part 7)

	Coeff. (1)	St. Error (2)
Heterogeneity × Drop Out Dummmy		
SES Group (Benchmark = High-SES)		
Medium-High × Rank 2	-0.041	(0.084)
Medium-High × Rank 3	-0.096	(0.115)
Medium-High × Rank 4	-0.111	(0.191)
Medium-High × Rank 5 or more	-0.253	(0.140)
Medium-Low × Rank 2	-0.018	(0.079)
Medium-Low × Rank 3	-0.020	(0.093)
Medium-Low × Rank 4	0.014	(0.108)
Medium-Low × Rank 5 or more	-0.192	(0.104)
Low × Rank 2	0.172	(0.080)
Low × Rank 3	-0.170	(0.122)
Low × Rank 4	-0.004	(0.137)
Low × Rank 5 or more	-0.042	(0.109)
Scholarship Status (Benchmark = Without Scholarship)		
With Scholarship × Rank 2	0.134	(0.072)
With Scholarship × Rank 3	0.030	(0.109)
With Scholarship × Rank 4	-0.012	(0.165)
With Scholarship × Rank 5 or more	0.129	(0.081)
Gender (Benchmark = Male)		
Female × Rank 2	-0.188	(0.060)
Female × Rank 3	-0.037	(0.074)
Female × Rank 4	-0.243	(0.096)
Female × Rank 5 or more	-0.143	(0.087)
Unobserved Heterogeneity (Benchmark = Type 1)		
Type 2 × Rank 2	-0.004	(0.065)
Type 2 × Rank 3	0.146	(0.098)
Type 2 × Rank 4	0.105	(0.124)
Type 2 × Rank 5 or more	0.102	(0.079)

NOTES. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

Table C-16: Probability to Graduate (Part 8)

	Coeff. (1)	St. Error (2)
Heterogeneity × Drop Out Dummmy		
GPA		
× Rank 2	0.020	(0.067)
× Rank 3	0.231	(0.103)
× Rank 4	0.038	(0.142)
× Rank 5 or more	0.116	(0.094)
Academic Track - Sciences		
× GPA × Rank 2	0.176	(0.081)
× GPA × Rank 3	-0.191	(0.125)
× GPA × Rank 4	0.106	(0.166)
× GPA × Rank 5	0.323	(0.113)
Technological Track		
× GPA × Rank 2	-0.208	(0.110)
× GPA × Rank 3	-0.241	(0.165)
× GPA × Rank 4	-0.331	(0.192)
× GPA × Rank 5	-0.457	(0.149)
Vocational Track		
× GPA × Rank 2	0.169	(0.106)
× GPA × Rank 3	-0.168	(0.224)
× GPA × Rank 4	-0.104	(0.235)
× GPA × Rank 5	0.058	(0.201)

NOTES. Estimates of Equation (B-2). Bootstrap standard errors in parentheses.

C.3 State Transitions: Offer Probabilities

Table C-17: Probability to Receive a New Offer

	Coeff. (1)	St. Error (2)
Panel A: Characteristics of the Current Offer		
Program Type (Benchmark = Bachelor)		
Prep-School	-0.445	(0.103)
Technical	0.130	(0.093)
Vocational	0.273	(0.100)
Other	-0.125	(0.102)
Program Major (Benchmark = STEM)		
Economics-Law	-0.022	(0.083)
Humanities	0.187	(0.086)
Services	-0.133	(0.078)
Location		
Distance	0.008	(0.019)
Same Catchment Area	0.066	(0.077)
Paris	0.056	(0.151)
Urban	0.142	(0.231)
Urban X same catchment	-0.194	(0.205)
Rent	-0.022	(0.051)
Rent X same catchment	0.013	(0.041)
Panel B: Heterogeneity		
SES (Benchmark = High)		
Medium-High	0.037	(0.057)
Medium-Low	0.091	(0.059)
Low	0.082	(0.068)
With Scholarship	0.008	(0.068)
Female	0.037	(0.042)
Type 2	0.091	(0.044)
High-School Track (Benchmark = Academic Tr. - Human. & Soc. Sci.)		
Academic Track - Sciences	-0.023	(0.051)
Technological Track	-0.027	(0.065)
Vocational Track	-0.236	(0.088)
GPA (Benchmark = Academic Tr. - Human. & Soc. Sci.)		
GPA	0.073	(0.037)
Academic Track - Sciences × GPA	-0.150	(0.051)
Technological Track × GPA	0.049	(0.066)
Vocational Track × GPA	0.284	(0.100)
Panel C: Programs Ranked Higher in ROL		
Number of Bachelor Prog.	0.213	(0.013)
Number of Prep-School Prog.	0.030	(0.013)
Number of Technical Prog.	0.031	(0.016)
Number of Vocational Prog.	0.030	(0.013)
Number of Other Prog.	-0.002	(0.017)
Panel D: Other Characteristics of Current Offer and Round		
Selectivity Index	-0.013	(0.004)
Round 2	0.041	(0.043)
Rank 3	-0.050	(0.041)
Rank 4	0.069	(0.057)
Rank 5 or more	-0.016	(0.067)
Constant	-0.828	(0.327)

NOTES. Parameters of the index of a binary logit on obtaining a new offer. Bootstrap standard errors in parentheses.

Table C-18: Probability to Receive a Specific Offer

	Coeff. (1)	St. Error (2)
Panel A: Common Component		
Program Type (Benchmark = Bachelor)		
Prep-School	-0.834	(0.184)
Technical	-0.437	(0.180)
Vocational	0.047	(0.182)
Other	-0.742	(0.186)
Program Major (Benchmark = STEM)		
Economics-Law	0.231	(0.176)
Humanities	0.384	(0.152)
Services	-0.316	(0.138)
Location Characteristics		
Distance	-0.127	(0.038)
Same Catchment Area	0.346	(0.101)
Paris	-0.673	(0.212)
Urban	-0.533	(0.367)
Urban X Same Catchment Area	0.887	(0.381)
Rent	0.067	(0.081)
Rent X Same Catchment Area	-0.192	(0.081)
Offer Rank 2	-0.384	(0.048)
Offer Rank 3	-0.403	(0.076)
Offer Rank 4	-0.394	(0.085)
Offer Rank 5 or more	-0.291	(0.075)
Panel B: Interactions with Program Selectivity Index		
SES Group (Benchmark = High)		
Medium-High	-0.046	(0.026)
Medium-Low	-0.055	(0.017)
Low	-0.045	(0.028)
With Scholarship	-0.022	(0.024)
Female	-0.009	(0.015)
Type 2	0.020	(0.017)
High-School Track (Benchmark = Academic Track - Humanities & Social Sciences)		
Academic Track - Sciences	-0.009	(0.021)
Technological Track	0.030	(0.026)
Vocational Track	0.019	(0.050)
GPA (Benchmark = Academic Track - Humanities & Social Sciences)		
GPA	0.035	(0.016)
Academic Track - Sciences × GPA	-0.069	(0.020)
Technological Track × GPA	0.040	(0.045)
Vocational Track × GPA	0.018	(0.050)

Notes. Parameters of the index of a conditional logit on higher-ranked alternatives, conditional on receiving a new offer. Bootstrap standard errors in parentheses.

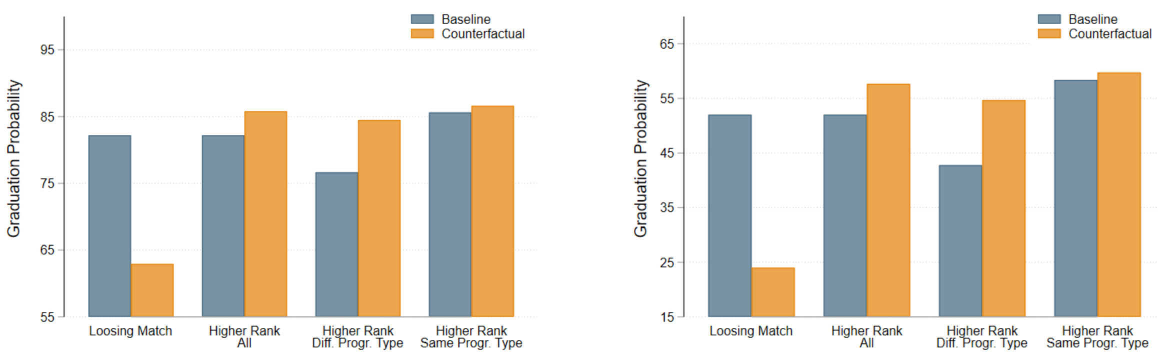
D Additional Results

Table D-1: Sequential Program Characteristics - Matched Students

	(1)
Share Improving Match	0.135
Panel A: Change in Program Type & Major	
Changed Type Only	0.141
Changed Major Only	0.058
Changed Both	0.267
Panel B: Other Program Characteristics	
Change in Distance	8.587
Probability Same Province	-0.071
Probability Same Catchment Area	-0.103
Probability Urban	0.019

Notes. This table focuses on students who would be admitted to a program both in the sequential and one round mechanism. It presents the share of students who are admitted to a higher-ranked program thanks to the sequential mechanism and, conditional on improving their admission outcomes, the changes between the program of admission in the sequential mechanism and in the one round mechanism.

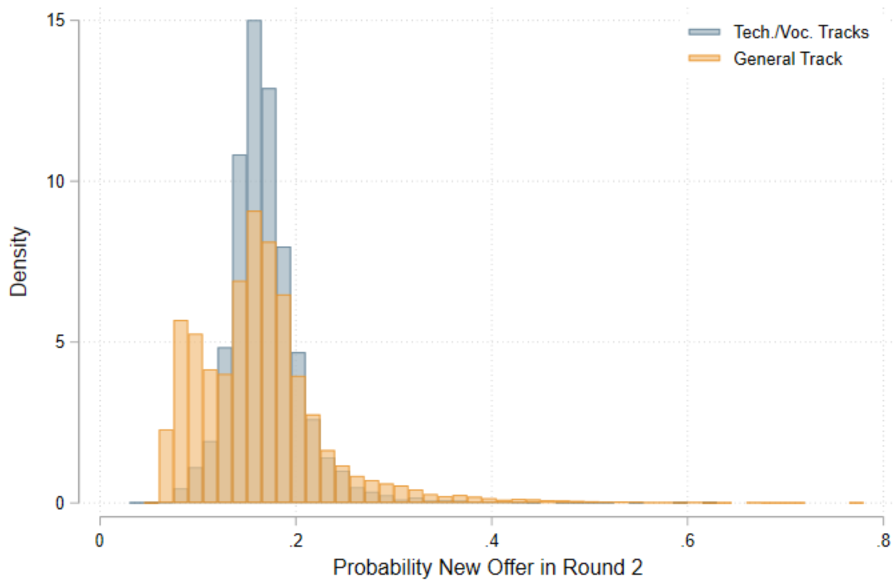
Figure D-1: Role of being matched and of matched rank on graduation outcomes



(a) Academic high school track **(b)** Technical and vocational high school track

Notes. This figure illustrates how accepting an on-platform offer—and the rank of that offer—affects students' likelihood of graduating from the higher education system. The left panel focuses on students from the academic track, while the right panel shows results for those from the technical and vocational tracks. Blue bars represent baseline graduation probabilities; orange bars show predicted probabilities after manipulating the offer received for the same students. The first two sets of bars present results for the full sample within each track. The third set breaks down outcomes for students whose higher-ranked program differs in major, program type, or both. The fourth set focuses on students who would instead be matched to a program that is observationally equivalent in both major and type.

Figure D-2: Distribution of Predicted Offer Probabilities in Round 2 for Students Without a Top-Ranked Offer in Round 1



Notes. This figure shows the distribution of predicted offer probabilities in Round 2 for students without a top-ranked offer in Round 1.

Table D-2: Offers by Groups

	% No Offer	Rank Offer
	(1)	(2)
SES Status		
High	0.08	2.43
Medium-High	0.12	2.09
Medium-Low	0.15	2.14
Low	0.20	2.10
High-School Track		
Academic	0.05	2.22
Tehnological	0.16	2.25
Vocational	0.43	2.17
Scholarship Status		
Eligible	0.17	2.20
Not-Eligible	0.13	2.22
Unobserved Type		
Type 1	0.11	2.26
Type 2	0.16	2.18

Notes. Column (1) shows the share of students without any round one offer, separately for students with different characteristics. Column (2) shows the average round one offer received, conditional on received one.

Table D-3: Offers by Groups

	Probability New Offer	
	Mean	St. Dev.
	(1)	(2)
SES Status		
High	0.15	(.065)
Medium-High	0.15	(.056)
Medium-Low	0.21	(.07)
Low	0.17	(.056)
High-School Track		
Academic	0.17	(.073)
Tehnological	0.16	(.051)
Vocational	0.18	(.065)
Scholarship Status		
Eligible	0.18	(.062)
Not-Eligible	0.17	(.069)
Unobserved Type		
Type 1	0.17	(.068)
Type 2	0.17	(.067)

Notes. This table shows the predicted probability to receive a new offer in round 2, conditional on having received an offer in the first round, separately for students with different characteristics.