Sequential College Admission Mechanisms and Off-Platform Options[a]

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Preliminary, please click here for the latest version.

Abstract

College admission platforms aim at achieving a balance between avoiding congestion and allowing for ex-post flexibility in students' matches. The latter is crucial as the existence of off-platform options implies that some students will drop out of the platform in favor of their outside option, freeing up seats in on-platform programs. Sequential assignment procedures introduce such flexibility, by creating a dynamic trade-off for students: they can choose to delay their enrollment decision to receive a better offer later, at the cost of waiting before knowing their final admission outcome. We quantify this trade-off in a setting in which waiting costs can be heterogeneous. We use rich administrative data on rank-ordered lists and waiting decisions from the French college admission system to estimate a dynamic model of application and acceptance decisions. We find that waiting costs are large, especially for students of low socio-economic status. Nevertheless, we find large welfare gains for all groups from using a multi-round rather than a more standard single-round system, as it increases the number of matches and enables students to enroll in more specialized programs.

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1 Introduction

Centralized college and school admission platforms are increasingly used around the world. This shift away from decentralized mechanisms has been driven by theoretical work (Abdulkadiroğlu & Sönmez, 2003), which has put forward the desirable properties of centralized allocation systems, in particular in avoiding congestion problems (A. E. Roth & Xing, 1997). However, real-world implementations of such centralized solutions often fail to deliver all the benefits which could theoretically be achieved. In particular, solving congestion problems by sending unique offers to students comes at the cost of a lack of ex-post flexibility, stemming from the existence of off-platform options (Kapor et al., 2024). Their presence implies that a number of students will end up rejecting the offer they received in favor of their outside option. This frees up seats in programs which might be preferred by some students to their current assignment. Welfare losses arise both for programs which end up with unfilled seats, and for students who are in a situation of justified-envy.

In this paper, we investigate the impact of allowing for ex-post flexibility in centralized matching mechanisms through the implementation of multiple single-offer rounds. In such systems, students first submit their rank-ordered list (ROL) to the platform, and then receive a unique offer, which they can choose to accept immediately, or hold on to, waiting for better opportunities in one of the following rounds. Despite being costless within the platform, the opportunity to wait for better offers comes at the cost of delaying the final admission decision. If students face some cost of waiting, sequential mechanisms introduce a dynamic trade-off. Students have to weigh the utility of receiving a potential better offer later against the disutility of waiting, which might encompass, for example, the cost of delaying the search for a student job or for an accommodation in the student's new location. The consequences of this dynamic trade-off on students' welfare are unclear, potentially heterogeneous, and call for an empirical investigation. On the one hand, the presence of a waiting cost might allow to take into account the strength of students' preferences even in a mechanism that allocates students to seats using a Deferred Acceptance algorithm. Indeed, only students who like a program very much would be willing to wait for the possibility to receive an offer. This might improve the quality of the resulting matches. On the other hand, sequential mechanisms might create inequalities if some students face a larger opportunity cost of time. This could in particular be the case of low socio-economic status (SES) students who may

be credit constrained or face additional search frictions on the housing market.

We quantify this equity-efficiency tradeoff using administrative data from the three-round French Admission Post-Bac (APB) system, which was used until 2018 to assign high-school graduates to public French universities. Data documenting applicants' decisions at each of round of this procedure, along with a dynamic model of applications and acceptance decisions, allow us to separately identify preferences for different programs and costs from waiting for better offers, following a two-step approach. In a first step, we use the ROL of students to identify the differences in utility between different programs for different students. In a second step, we estimate the probability for students to receive a particular offer, and recover the waiting costs and drop-out utility by rationalizing within a dynamic framework their choices to accept an offer, delay or drop out of the admission platform. Detailed information on ROLs and offers and choices in the different rounds allows us to account for both observed and unobserved student heterogeneity. We implement a tractable Expectation-Maximization based estimation method by adapting the Conditional Choice Probability (CCP) approach to our context (Arcidiacono & Miller, 2011).

Estimated preferences for programs and waiting costs can then be used in counterfactual exercises to explore the distributional consequences of waiting costs, and the welfare effects of sequential procedures. Notably, comparing total student welfare as well as the welfare gap between low-SES and high-SES students under the baseline procedure and a single-round assignment procedure makes it possible to quantify the equity-efficiency trade-off brought by the sequential admission procedure, between increased match quality and heterogeneous costs of waiting.

We obtain three main sets of results. First, our estimates point to large waiting costs, especially so among low-SES students. These costs are of a similar magnitude as the utility differences between types of colleges or majors, thereby causing sub-optimal matches. Second, despite the aforementioned frictions, all groups of students benefit from a sequential matching mechanism, compared to a (counterfactual) one-round mechanism. On average, the status quo sequential system provides a gain equivalent to enrolling 354 kilometers closer to home. Zooming in on the 52% of students who do not receive their first-ranked alternative in Round 1, this increases to a sizeable distance of 860 kilometers. This large welfare increase is driven by the subgroup of students who, at the end of Round 1, exercise the option to delay.

These students, who have a positive continuation value, net of waiting costs, benefit from the sequential nature of the admission mechanism. Third, we document the existence of substantial impacts associated with the sequential mechanism on offers as well as acceptance decisions. These effects reflect two main channels, namely an increase in the number of successful matches, along with a match quality improvement. Vocational and technical high-school students are the most likely to gain a match from the sequential mechanism, while general-track students are more likely to improve their match. Taken together, this results in a 5.9% overall increase in graduation rates.

While we do not directly simulate choices under a decentralized admission system, our analysis also speak more generally to the arbitrage between decentralized and centralized admission systems. Taking into account dynamic considerations and potential heterogeneity in waiting costs across students helps highlight other dimensions of the students' application decisions which are relevant to the choice of the admission mechanism. For example, heterogeneity in waiting cost would underline that decentralized admission systems might be particularly detrimental to disadvantaged students. This is especially true given the fact that academic ability and parental income are often positively correlated, meaning that, in decentralized markets, high-SES students will receive multiple offers early, and subsequent offers to low-SES students will only be made once high-SES students will have finalized their admission decision. Low-SES students might then be pushed to accept the lower quality early offers they received while they could have been admitted to a preferred option, or decide to wait but can only find low quality affordable accommodations.[1]

Related literature. A couple of other recent studies have investigated the properties of sequential assignment mechanisms, that is, mechanisms in which applicants are brought to interact multiple times with the clearinghouse (Luflade, 2018; Chen & Pereyra, 2019; Grenet

[1]In fact, this is exactly what was feared when the French Ministry of Education decided to switch from APB, a centralized admission systems with three rounds of admission, to Parcoursup, a decentralized platform where students can receive multiple offers, in 2018. A report from the French Assemblée Nationale, in 2017, indeed warned about the fact that, in Parcoursup, disadvantaged students would be harmed as they will be more likely to receive offers later and would then face difficulties to find affordable accommodations. Some newspaper articles confirm that the platform change has triggered issues for students assigned very late in the procedure to find an accommodation before the academic year starts.(see https://www.marianne.net/societe/parcoursup-la-recherche-d-un-logement-ou-l-autre-galere-des-etudiants-en-attente, or https://www.liberation.fr/france/2018/05/29/quand-parcoursup-complique-la-recherche-d-un-logement-social$_$1655070/). This paper provides a framework allowing to partly capture such considerations.

et al., 2022; Bó & Hakimov, 2022). Focusing on the timing of offer acceptance, our paper is closest to Grenet et al. (2022), who find that students participating in the German university admission system are more likely to accept the earliest offer they receive. They rationalize this fact using a model of learning: at the time of application, students imperfectly know programs' qualities; at each period before the final-acceptance period, they decide whether to pay a cost to learn about one program's quality and, if so, optimally decide which program to learn about; in a sequential-offer setting, students are more likely to learn first about (and then choose) the program they receive an offer from. While allowing for students' preferences to evolve throughout their dynamic interactions with the mechanism, we allow for an alternative channel and investigate the role of waiting costs in decision-making in a sequential-offer mechanism. We estimate a dynamic model of application and offer acceptance to evaluate the welfare effects of the sequential procedure.

Our paper also examines the consequences of the co-existence of a centralized admission platform and off-platform options. As such, our analysis complements recent work by Kapor et al. (2024), who study the welfare impacts of off-platform options in Chile, together with the presence of aftermarket frictions generated by the decentralized system of waitlists. They quantify the welfare cost of the presence of off-platform options through a counterfactual scenario where additional programs are added to the platform. While this counterfactual scenario can be understood as a first-best solution, it might be difficult in practice to incentivize programs to join the centralized platform.[2] In contrast, we focus in this paper on the evaluation of mechanisms with sequential rounds as an easy-to-implement solution aimed at mitigating the cost of off-platform options.

More broadly, and beyond the school choice setting, this paper adds to a small but growing set of papers modeling the dynamic considerations induced by centralized assignment mechanisms (Agarwal et al., 2021; Waldinger, 2021; Larroucau & Ríos, 2021; Huitfeldt et al., 2024). We contribute to this literature by quantifying and evaluating the welfare consequences of the dynamic trade-off that students face, in the presence of waiting costs, when deciding whether to accept an admission offer or instead delay acceptance by participating to the next round.

Our paper also contributes to the large and growing literature on the determinants of

[2]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.

students' higher education choices, in particular joint choice of institution and field of study (see Altonji et al., 2016; and Patnaik et al., 2021 for reviews of this literature). We contribute to this literature by leveraging the sequential nature of the centralized APB college admission platform to quantify preferences for the different programs and the cost of waiting for the opportunity to receive an offer from a preferred program. This, in turn, allows us to explore the welfare implications of the dynamic trade-offs associated with this type of sequential college assignment mechanism. By doing so, our paper highlights the important role played by external factors and constraints, such as the ones generating these waiting costs, in students' higher education decisions.[3]

The remainder of the paper is organized as follows. Section 2 describes the French higher education system and its centralized college admission procedure, Admission Post-Bac (APB). Section 3 presents the data and some descriptive evidence of the dynamic trade-off faced by students. Section 4 delineates our structural model of students' dynamic application decisions, while Section 5 discusses our identification and estimation strategy. Section 6 presents the estimation results as well as the counterfactual exercises we perform. Finally, Section 7 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.

2.1 The French Higher Education Market: a Semi-Centralized System

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.[4] The content of this exam is determined by students' choice of

[3] See also recent work by Humphries et al. (2023) who study and estimate a model of college investments in the presence of a centralized college application process.

[4] Appendix A provides more details about the high school system in France.

track (*general*, *technological* or *vocational*) and high-school major.[5]

There are five types of higher education programs available to students. First, students can apply to three-year university programs, offering to graduate with a bachelor's degree. Second, students can apply to two-year elite programs. These programs are highly selective and prepare students to take competitive exams for admission to the most prestigious public and private higher education institutions. Once enrolled in these elite schools, students will then typically continue their education to earn a master's degree. Third, there are also programs offered by engineering and business schools. Finally, students can also enroll in short-term programs, providing more technical and vocational training. The latter are divided between two-year technology-oriented programs, tailored to train mid-level technical professionals, and two-year vocational programs, with a stronger emphasis on internships.

As in many countries, the application and admission procedures in France can be described as semi-centralized.[6] The majority of 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. In particular, 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.[7] These institutions typically want to retain a complete autonomy on their admission procedure.

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-

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

[6] For example, 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., 2024). In Brazil, in 2017, 133 higher education institutions participated in the centralized admission system, out of 2,448 private and public institutions (Machado & Szerman, 2021). In Germany, two centralized clearinghouses allocating university seats co-habit (one administering programs in medicine-related majors only), but program participation is not mandatory (Grenet et al., 2022).

[7] We provide details on the off-platform programs in Appendix A.2

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. This makes it key to design a centralized procedure allowing to 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 87% of the first-year higher education programs. Students in their final high-school year register on this platform and are asked to submit rank-ordered lists of up to 36 programs, with a maximum of twelve per *type* of program. The five *types* of programs —Bachelor programs, technical programs, prep-school programs, vocational programs, and programs in engineering and business schools— are described in Table A-1.

Each program then rank applicants following their priorities. From the perspective of students, no priority score is known at the time of application, nor at any point during or after the process. The nature of priorities used to rank applicants depend 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. On the other hand, the priorities of bachelor programs are regulated by law: they are not allowed to use students' academic performance as a determinant of their priority. Instead, these programs have to rank applicants based on coarse priority groups defined with respect to the applicant's residential location and the absolute rank of the program in the applicant's ROL.[8] Then, a random lottery number is used to rank applicants within coarse priority groups. It is important to know that, in 2015, while the APB system was in use, the criteria used to determine Bachelor programs' priorities were unknown to the public. The use of lottery numbers and, more importantly, the role of their own rank-ordered lists in the determination of their priority to programs was unknown to students in the year we study, who were simply aware of the within-region advantage.

Given the students' rank-ordered lists and the priorities set by each program, matches

[8]Specifically, groups are defined depending on whether or not the student lives in the region where the program is located. See Figure A-1 for the map of the regions used for the construction of priorities (*académies*).

are determined by the clearinghouse using a college-proposing deferred acceptance (DA) algorithm. The limited amount of information provided to students at the time of application sets apart the French APB system from many other centralized school assignment mechanisms that have been studied in the literature. Not only priorities and their determinants but also the very algorithm used by the clearinghouse are unknown to students.[9] As a matter of fact, the only guideline provided to students was to report their preferences truthfully in their ROLs.

A key feature of the centralized admission platform is that it is designed to introduce some flexibility to students' enrollment 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 ran several times in order to redistribute seats left vacant by students who applied to the centralized platform before ultimately turning down a program's offer. Specifically, after receiving a first assignment from the platform, students can choose between three options. They can i) *accept* the assignment immediately and proceed with enrollment, ii) refuse it and *drop out* of the platform, thereby returning her assignment to the vacancy pool, or iii) decide to *delay* their decision and participate in the next round, that is, hold on to their assignment and maintain her applications to the programs ranked higher than her current offer in her ROL.[10] The matching algorithm is then run again by the clearinghouse, excluding students who dropped out and using the same ROLs and priorities as in the first round, to assign the remaining vacancies to unmatched students and to those who chose to delay their decision. 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 in 2015, which is the year our empirical analysis focuses on.

[9]Note also that "past admissions cutoffs" available to applicants in many other context are not disclosed in this setting.

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



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 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 details the characteristics of all on-platform programs, such as their type, major, and location.[11] Finally, it provides detailed information on all activities within the platform: the rank-ordered list submitted by each applicant, their assignment offer in each round (if any), as well as their decisions (accept, drop out, or delay) for that round.[12]

We focus our attention on the 2015 assignment procedure and further restrict the sample to students participating in the college assignment procedure for the first time in 2015.[13] Table A-2 describes applicants' characteristics as well as their final assignment. Students submit on average slightly less than seven applications. Their final assignment is on average ranked 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 when we explore the benefits to choosing the option to *delay*.

The second administrative dataset we use is a census of all students enrolled in the

[11] 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.

[12] Details about the data sources and the definition of key variables are provided in Appendix A.2.

[13] We also exclude students who completed high school outside of mainland France, whether it is abroad or in the French overseas regions.

French higher education system until their exit. Each year, it records the institution where the student is enrolled, the major studied and details about the diploma delivered. We use this information to recover whether a student drops out from the higher education system and, if not, with what degree they graduate. Importantly, this dataset can be merged with the one described above and contains both on- and off-platform programs.

3 Descriptive Evidence

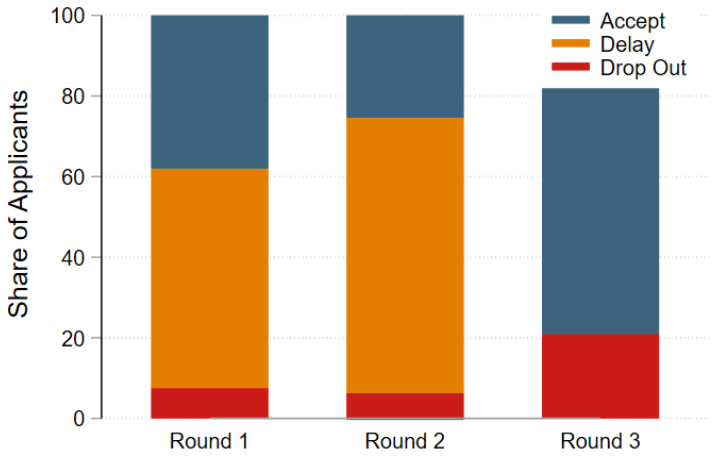
This section documents students' behavior across the three admission rounds, focusing on their use of the option to delay. We show that there are gains from delaying, as a substantial fraction of the students who *delay* eventually receive a higher-ranked offer in a subsequent round. Yet, we also document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

Fact 1: The use of *delay* is not systematic. We first document that students do not systematically 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 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 participants choose to delay, while about 25% accept their assignment. In the third round, when students cannot choose to delay, 85% of participants accept their assignment while the rest drops out.

Such patterns are consistent with the fact that it may be costly for students to wait before receiving their final assignment, such that they have to arbitrage between these waiting costs and the option value of delaying, which gives them the opportunity to receiving an offer from a higher-ranked program in a subsequent round. We explore next the benefits associated to delaying, before turning to potential drivers of waiting costs.

Fact 2: *Delaying* is associated to substantial benefits. Table 1 illustrates the expected benefits of choosing the delay option. Eighteen percent of the students choosing to

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.

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. The latter is ranked on average 2.73 ranks above the offer they hold on to at the end of round 2.

Table 1: Assignment Improvements from Delaying

	Mean
Received Better Offer	
Round 2	0.18
Round 3	0.19
Mean Rank Improvement	
Round 2	2.48
Round 3	2.73

NOTES. This table reports the share of students receiving a higher-ranked offer, conditional on delaying in the previous round.

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

$$Y_i = \beta_0 + \beta_1 \mathbf{1}[i \text{ received a new offer at Round 2 or 3}] + \mathbf{X}_i'\beta_2 + \epsilon_i \tag{1}$$

where $\mathbf{1}[i$ received a new offer at Round 2 or 3] 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) his Round-1 offer, and 0 otherwise; and $\mathbf{X}_i$ is a vector of individual characteristics. Columns (1) and (2) of Panel A show estimates obtained for β_1 when estimating Eq. (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 those students who received a first round offer *and* choose to delay in the first round. Results show that those who receive a later-round offer are 3.7 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) show similar estimates but 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 2022-23 academic year. Estimates show that those who receive a later-round offer are three percentage points less likely to leave the higher-education system without a degree than the average students who delay in the first round. Columns (5) and (6) show that 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.

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	0.034	0.037	-0.028	-0.030	-0.016	-0.023
	(0.003)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Baseline	80.60	80.60	30.01	30.01	20.55	20.55
Obs.	78,884	78,884	78,884	78,884	63,582	63,582
Panel B: Students Without Offer in Round 1						
Received Later-Round Offer	0.286	0.236	-0.193	-0.116	-0.111	-0.054
	(0.003)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Baseline	34.56	34.56	73.45	73.45	46.77	46.77
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) to (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. The students' high-school track, high-school GPA and the rank of the offer received in round one (Panel A only) are controlled for in Columns (2), (4), and (6).

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 an offer in the first round; 25% of them receive an offer in a later round. We estimate Eq. (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 not to earn a degree (Column (4)) than the average student who did not receive an offer in the first round. Column (6) shows that the 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 do enroll in some higher-education program at some point.

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. 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).

Table 3: Share of eligible students choosing to *delay*, by SES

	Round 1	Round 2
	(1)	(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.

Turning to heterogeneity across offer characteristics, Table 4 shows that holding an offer from a lower-ranked program is associated with a larger probability to delay acceptance. This is consistent with the fact that the option value of delaying is larger when there is a larger set of programs from which the student may get an offer from in the next rounds.

Finally, we show suggestive evidence that students' probability to use delay depends on the geographic location of current and potential future offers. For simplicity, to produce Table

Table 4: Holding an offer from a lower-ranked program is associated with a larger probability to delay acceptance.

	Round 1 (1)		Round 2 (2)	
Rank 3	0.107	(0.004)	0.064	(0.006)
Rank 4	0.170	(0.004)	0.109	(0.008)
Rank 5	0.198	(0.005)	0.123	(0.010)
Rank 6	0.239	(0.005)	0.147	(0.011)
Rank 7	0.258	(0.006)	0.169	(0.013)
Rank 8	0.277	(0.007)	0.167	(0.015)
Rank 9	0.271	(0.008)	0.172	(0.018)
Rank $\geq$ 10	0.305	(0.005)	0.201	(0.021)
Higher-Rank Ctrls	Yes		Yes	
Top-Rank Ctrls	Yes		Yes	
Demographics Ctrls	Yes		Yes	
Nb. Students	141,230		73,587	

The table shows the increase in the probability to delay acceptance associated with holding an offer from one's jth-ranked program relative to holding an offer from one's second-ranked program, controlling for observed characteristics of the current offer and the student's top ranked program, as well as for the student's demographics. The sample is restricted to those in a position to choose the delay option, that holding an offer that is not from their top-ranked program. The set of demographic controls include gender and SES dummies. The regression also includes controls for the type and major of the student's top-ranked program, and for the number of programs of each type and each major ranked higher than the current offer. Standard errors are shown in parentheses.

5, we restrict our attention to students holding an offer from their second-ranked program, and for whom the potential future offer they may choose to wait for is therefore unambiguous —it can only come from their top-ranked program. In Round 2 (Columns (3) and (4)), the highest probabilities to delay are observed for those whose potential future offer is in their home region. This could be consistent with the fact that at the end of Round 3, it may be too late for some students to find an (affordable) accommodation away from home. Programs away from home are therefore less worth waiting for as time passes. In contrast, programs in one's home region remain more valuable even late in the process as they are less likely to require relocation out of the family home.

Results relative to Round 1 are less striking, which suggests the presence of composition effects —those choosing delay in the second are different from those choosing delay in the first round— and that waiting costs or early-acceptance utility vary over time. Estimating

the structural model we propose in the next section will shed light on these factors.

Table 5: Probability to delay as a function of location of current and potential future offers

	Round 1		Round 2	
	(1)	(2)	(3)	(4)
Home/Not home	-0.005	-0.014	-0.029	-0.055
	(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)	0.031	0.011	-0.050	-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 Ctrls	No	Yes	No	Yes
Top-Rank Ctrls	No	Yes	No	Yes
Demographics Ctrls	Yes	Yes	Yes	Yes
Obs.	51,229	51,229	21,044	21,044

This table shows the change in the probability to delay associated to changes in the location of the current and potential future offer, relative to when both are located in the applicant's home region. The sample is restricted to applicants holding a offer from their second-ranked program. The set of demographic controls include gender and SES dummies. The regression also includes controls for the type and major of the student's top-ranked program, and for the number of programs of each type and each major ranked higher than the current offer. *Reading:* Among students holding an offer from their second-ranked program, and potentially expecting an offer from their top ranked program, the current offer being in one's home region while the expected offer is not is associated with a probability to delay lower by half a percentage point relative to when both programs are in the student's home region.

4 A Model of Students' Dynamic Application Decisions in a Sequential Admission Mechanism

We build a structural model of students' decisions in a sequential admission mechanism as the one implemented in France. It encompasses the different decision-making steps through which the student will go through on the platform. The model thus has two stages. In the first stage, students submit their ROL, based on their preferences between the different programs. The second stage of the model is dynamic: in a given round, students receive an offer and choose one of the three (or two in the last round) different answers available on the platform.

4.1 Stage 1: Rank-Ordered List Submission

When they connect to the platform, students are asked to submit a rank-ordered list of the programs they want to apply to. We assume students list truthfully their preferences, as was explicitly recommended on the platform. We discuss this assumption at the end of this section.

Utility. A student i derives utility u_{ij} from enrolling in program $j \in \mathcal{J}$, where $\mathcal{J}$ is the set of programs available on the platform. We assume students rank programs according to the utility of being matched to them and a random shock:

$$u_{ij} + \eta_{ij} = u_j(S_i, \tau) + \eta_{ij}.$$

The utility is a j-specific function of a $L \times 1$ vector of observed characteristics S_i and a type τ. We assume a distribution of discrete types with finite support. The shock η_{ij} takes into account that they might have a "trembling hand".

Revealed ROL. Let $\bar{R}$ be the maximum length of submitted ROLs, and d_{ir}^{ROL} denote the program ranked in position $r \in \{1, ..., \bar{R}\}$ on student i's ROL. Assume an extreme value type 1 distribution on η_{ij} with scale parameter σ. Students revealing their preferences, the likelihood of observing one's ROL is given by the well-known exploded (or rank-ordered) logit probabilities:

$$\frac{\exp(u_{id_{i1}^{ROL}}/\sigma)}{\sum_{j\in\mathcal{J}}\exp(u_{ij}/\sigma)} \times \frac{\exp(u_{id_{i2}^{ROL}}/\sigma)}{\sum_{j\in\mathcal{J}\setminus\{d_{i1}^{ROL}\}}\exp(u_{ij}/\sigma)} \times ... \times \frac{\exp(u_{id_{iR_i}}/\sigma)}{\sum_{j\in\mathcal{J}\setminus\{d_{ik}^{ROL}\}_{k=1}^{R_i-1}}\exp(u_{ij}/\sigma)} \tag{2}$$

Note that many students do not submit a complete ranking. This could be the result of an effort cost in submitting a long list, against a limited gain if the list already contains safe choices. An alternative explanation is that the outside option (i.e. not attending a program in $\mathcal{J}$) is preferred over the unranked alternatives. We remain agnostic about the underlying reason by not including the outside option here and therefore only consider ranks between programs on the platform $\mathcal{J}$.

Remark. As described in Section 2, no information was disclosed to the public about either the algorithm used by the clearinghouse or the existence of strategic incentives, which stem from the fact that the applicant's priority for any Bachelor program is a function of the program's rank in her ROL. The only available guideline to applicants was to rank programs in order of preference. As a consequence, it seems reasonable to assume that students truthfully report their preferences in their ROL. This assumption in the setting of this paper is in line with the argument made in the literature that, even though the mechanism is not strategy-proof, truth-telling or a simple strategy close to truth-telling (truncation) may be the best action participants can take when they have limited information about the mechanism or others' preferences. A. Roth & Rothblum (1999) highlight that even in the simple case of the school-proposing DA, identifying profitable deviations from truthful reporting requires students to have more information than they often have in practice. Typically, a given manipulation is profitable under certain priorities and preference profiles for other applicants, but will yield a strictly worse outcome than truthful reporting given another state of the world. It is then crucial for a student to have good information about priorities and others' preferences —which students in our setting do not have— to be able to identify whether a particular action will be profitable. More recently, Troyan & Morrill (2020) formalize the concept of "obvious" profitable manipulations as profitable manipulations that can be identified as doing better than truthful reporting for agents who only know the range of outcomes that can result from each of their actions, that is, what would happen in the 'best-case scenario' and in the 'worst-case scenario' following their possible actions. They show that, in that sense, the school-proposing DA is not obviously manipulable.

4.2 Stage 2: Dynamic Model of Students' Enrollment Decisions

In the second stage of the model, students receive offers from the platform and can decide to match. Matching can occur in different rounds $t = \{1, 2, 3\}$. At the start of each round, each student receives a unique offer $j_t \in \mathcal{J} \cup \{0\}$, with $j_t = 0$ denoting no offer of a program. If $j_t \neq 0$ and $t < 3$, they can choose between options $k = \{1, 2, 3\}$ to maximize their expected lifetime utility. These denote respectively accepting the offer, delaying the decision, or dropping out from the platform. In the last round ($t = 3$), applicants can only decide to accept ($k = 1$) or drop-out from the platform ($k = 3$). If the student has not received any offer yet ($j_t = 0$), they can only wait and continue to the next round ($k = 2$) or drop out

from the platform ($k = 3$). The expected lifetime utility is formalized by choosing the option d_{it}^{DDC} that yields the highest value of $v_{ikt} + \epsilon_{ikt}$, with v_{ikt} a conditional value function, and ϵ_{ikt} a random shock, revealed to students in round t. We now discuss the conditional value functions of each option.

Accept ($k = 1$). Accepting the offer yields the utility of being admitted to program j_t:

$$v_{i1t} = u_{j_t}(S_i, \tau) + w_{j_t}^{(t)}(S_i, \tau) \tag{3}$$

with $w_{j_t}^{(t)}(S_i, \tau)$ 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.

Delay ($k = 2$). A student can also 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: $\omega_{it} = \omega_t(S_i, \tau)$. This captures the impatience of students, and is unrelated to the characteristics of the student's offer or listed programs. This cost of waiting can be financial, but it can also reflect psychic costs. An impatient student would have high (psychic) waiting costs; a student who tends to procrastinate would have low (or even negative) such costs (Akerlof, 1991). In addition to waiting costs, the value of waiting also depends on the continuation value that captures their (weakly) improved offer in the next round, yielding the conditional value function:

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

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 Ω_{it}. $\mathcal{R}_i^{j_t}$ is the set of options in $\mathcal{R}_i$ that are ranked above j_t. $\bar{V}_{it+1}(\Omega_{it}, j_{t+1})$ is the expected value of behaving optimally in the next round, conditionally on their current information and the offer received, j_{t+1}. We assume students keep track of their time-invariant individual characteristics S_i, type τ, ROL $\mathcal{R}_i$ and the time-varying round t and offer j_t, that is, $\Omega_{it} = (S_i, \tau, \mathcal{R}_i, t, j_t)$.

Drop out ($k = 3$). Finally, the student can decide to drop out from the platform, associated with utility:

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

where $u_{0t}(S_i, \tau)$ captures the utility of their outside option.

Choice sets and solving the model. Assuming mean-zero extreme value type 1 taste shocks with scale normalized to 1, we can derive the choice probabilities in each round:

$$\Pr(d_{it}^{DDC} = k|\Omega_{it}) = \frac{\exp(v_{ikt})}{\exp(v_{i1t}) + \exp(v_{i2t}) + \exp(v_{i3t})} \tag{6}$$

The choice problem stops when students choose one of the terminal actions ($k = 1$ or $k = 3$). Note that in $t = 3$, only these two options are available (i.e. $v_{i23} = -\infty$) so the model becomes essentially static and can be solved for each realization of the time-varying state variable j_3. The rest of the model can be solved by backward induction, taking into account the expected value of behaving optimally in the future. This is facilitated by the closed-form solution resulting from the extreme value distribution:

$$\bar{V}_{it+1}(\Omega_{it}, j_{t+1}) = \ln(\exp(v_{i1t+1}) + \exp(v_{i2t+1}) + \exp(v_{i3t+1})) \tag{7}$$

Substituting Eq. (7) into Eq. (4) allows us to write the conditional value functions in $t = 2$, up to the data, utility parameters and state transitions. We can proceed in an analog way for $t = 1$. Note that not every alternative is always available to each applicant, in which case we set the value of the alternative at that round to $v_{ikt} = -\infty$. For instance, students who get an offer from their top-ranked offer are not allowed to choose *delay*; and a student with no offer cannot choose *accept*. In addition, the alternative *delay* is not available to anyone in Round 3.

4.3 Graduation

We model student i's graduation outcome using a variable d_i that may take one of $M + 1$ distinct values. Namely, either i does not graduate from the higher education system ($d_i = 0$) or they earn a higher-education degree ($d_i = m \in \{1, 2, \ldots, M\}$), which is characterized by a type and major pair. We use for this part of the framework a reduced-form approach, and

model student graduation outcomes d_i as following a multinomial logit:

$$d_i = m \in \{0, 1, \ldots, M\} \text{ iff } h_m(S_i, \tau, j) + e_{im} > h_{m'}(S_i, \tau, j) + e_{im'} \ \forall m' \neq m. \tag{8}$$

where $h_m(S_i, \tau, j)$ is a graduation index and e_{im} is an extreme value type 1 distributed shock. The exact parameterization of the model is shown in Equation (B-2) in Appendix B. h_m depends on student i characteristics, including high-school GPA and track; whether student i got matched with a program j by the assignment mechanism. h_m also depends on the major and type of program j, and the rank of j on i's ROL.

5 Identification and Estimation

We first discuss the identification and parametrization of the model. We then discuss estimation for the case where type τ is known, how to estimate the model without solving it (CCP estimation), and how to allow τ to be unobserved by the econometrician.

5.1 Identification

We first discuss the case when types are observed and then generalize.

Program utility. The program utility $u_j(S_i, \tau)$ for $j \neq 0$ is identified up to scale using the ROLs, i.e. we identify $\tilde{u}_{j_3}(S_i, \tau) \equiv \frac{1}{\sigma} u_{j_3}(S_i, \tau)$. Without loss of generality, we normalize the utility of an arbitrary reference alternative to be 0. In practice, this corresponds to a hypothetical Bachelor-STEM program with other characteristics (such as distance) set to 0.

Scale and dropout in terminal period. Note that at $t = 3$, students can only choose between accepting the offer they hold, to get $v_{i1,t=3} = u_{j_3}(S_i, \tau)$, and dropping out, which yields $u_{03}(S_i, \tau)$. Mapping the choice probabilities of this static choice problem into the utility functions, we have:

$$\begin{aligned} \ln \Pr(d_{i3}^{DDC} = 1|\Omega_{i3}) - \ln \Pr(d_{i3}^{DDC} = 3|\Omega_{i3}) &= v_{i13} - v_{i33} \\ &= \sigma \tilde{u}_{j_3}(S_i, \tau) - u_{03}(S_i, \tau), \end{aligned} \tag{9}$$

From there, let z be a program characteristic with $\frac{\partial \tilde{u}_{j_3}(S_i,\tau)}{\partial z} \neq 0$ that is excluded from u_{0t}. Taking derivatives and re-arranging yields:

$$\sigma = \frac{\partial(\ln \Pr(d_{i3}^{DDC} = 1|\Omega_{i3}) - \ln \Pr(d_{i3}^{DDC} = 3|\Omega_{i3}))/\partial z}{\partial \tilde{u}_{j_3}(S_i,\tau)/\partial z}, \tag{10}$$

where probabilities are observed and $\frac{\partial \tilde{u}_{j_3}(S_i,\tau)}{\partial z}$ is identified from ROLs. Eq. (10) therefore identifies σ, and Eq. (9) then identifies the drop-out utility $u_{03}(S_i,\tau)$.

Other primitives in the dynamic model. While state transitions are identified non-parametrically, payoffs in dynamic discrete choice models are identified only after assuming a distribution on the taste shocks, specifying the discount factor, and normalizing the utility of one alternative in each state (Magnac & Thesmar (2002)). We assume a mean-zero taste shocks are drawn from an extreme value type 1 distribution and we normalize the discount factor to 1 (as different stages follow each other quickly). At this stage, note that the early acceptance utility depends only on the characteristics of the accepted offer and their interactions with individual characteristics. Waiting costs and drop-out utilities at $t < 3$ only depend on individual characteristics. Conceptually, waiting costs capture the disutility students derive from not knowing their final outcome yet, given that they are currently assigned the benchmark program, while the early acceptance advantage captures how program characteristics can change their willingness to wait. The early acceptance utility is therefore identified by the systematic variation in students' probability to accept their offer as a function of the offer attributes and their interactions with student characteristics. On the other hand, waiting costs are identified by the baseline probability of students waiting, irrespective of the offer they hold. Conceptually, we interpret waiting costs as capturing the disutility students derive from not being done with the assignment process, while the early acceptance advantage captures the fact that some offers are more valuable when they are accepted early, and may therefore students' willingness to wait.

Unobserved types. The unobserved types are identified as 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. The type-specific intercept in the value of the outside option is identified by different probability to drop out across types. The type-specific parameters in the early-acceptance utility rationalize

the systematically different probabilities to accept across types along the distance, main city, and rent attributes of the offer. Type-specific parameters in the utility function are informed by two type of variation. They rationalize different probabilities, across types, to include programs with certain characteristics in one's ROL. Importantly, because they create differences in the intensity of preferences for programs, they are also informed by different probabilities to delay acceptance as a function of the characteristics not only of the offered programs, but of the higher-ranked programs in the ROL as well. The type-specific waiting cost intercept rationalizes the residual difference in probabilities to accept/wait across types after accounting for the differences in the attributes of the offer and of the higher-ranked program. Fundamentally, different probabilities to delay, across students, conditional on individual, offer, and ROL characteristics reveal differences in the intensity of preferences for programs, which operate through unobserved types in our model. These differences therefore inform about the distribution of types in the population.

5.2 Parameterization

In practice, for estimation, we impose a flexible parametric structure. While these parametric restrictions are not needed for identification, these yield substantial precision gains.

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

$$
\begin{aligned}
u_j(S_i,\tau) = \sum_k \mathbf{1}[\text{Prog_Type}_j = k] \cdot \Big(\alpha_0^{(k,\tau)} + \alpha_1^{(k)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4}\alpha_2^{(k,s)}\mathbf{1}[\text{SES}_i = s] + \dots \\
\alpha_3^{(k)}\text{GPA}_i + \sum_{s=2}^{4}\mathbf{1}[\text{Hs_Track}_i = s](\alpha_4^{(k,s)} + \alpha_5^{(k,s)}\text{GPA}_i)\Big) \\
+ \sum_k \mathbf{1}[\text{Field_Study}_j = k]\Big(\beta_0^{(k,\tau)} + \beta_1^{(k)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4}\beta_2^{(k,s)}\mathbf{1}[\text{SES}_i = s] + \dots \\
\beta_3^{(k)}\text{GPA}_i + \sum_{s=2}^{4}\mathbf{1}[\text{Hs_Track}_i = s](\beta_4^{(k,s)} + \beta_5^{(k,s)}\text{GPA}_i)\Big) \\
+ \gamma_1\text{Distance}_{ij} + \gamma_2\mathbf{1}[\text{Same_Catchment}_{ij}] + \gamma_3\mathbf{1}[\text{Paris}_j] \cdots \\
+ \mathbf{1}[\text{Main_City}_j]\left(\gamma_4 + \gamma_5\mathbf{1}[\text{Same_Catchment}_{ij}]\right) + \text{Rent}_j\left(\gamma_6 + \gamma_7\mathbf{1}[\text{Same_Catchment}_{ij}]\right)
\end{aligned}
\tag{11}
$$

where Hs_Track_i denotes student i's high-school track; Distance_{ij} is the kilometer distance between i's home and the location of program j; Rent_j is the average rent in program j's location; and $\mathbf{1}[\text{Same_Catchment}_{ij}]$, $\mathbf{1}[\text{Main_City}_j]$, and $\mathbf{1}[\text{Paris}_j]$ are indicators taking the value 1 if j is located in the same catchment area as i's home, in major city, and in Paris, respectively. [14] This set of variables flexibly captures the location characteristics of programs. We allow preferences for program types and majors to vary with both observed individual characteristics (demographics, high-school performance and track) and unobserved type. We consider five program types (Bachelor program, vocational, technical, 2-year prep school, and other) and five broad fields of study (STEM, Econ./Law, Humanities, Production, and Services).[15] For the sake of brevity, we defer the parameterization of $w^{(t)}(S_i, \tau)$, which captures the possible change in preferences for programs across periods, to Appendix B.

Waiting costs. We model the utility from waiting as follows:

$$-\omega(S_i, \tau) = c_0^{(\tau)} + c_1 \mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4} c_2^{(s)} \mathbf{1}[\text{SES}_i = s] + c_3 \text{GPA}_i + \ldots$$
$$\sum_{s=2}^{4} \mathbf{1}[\text{Hs_track}_i = s](c_4^{(s)} + c_5^{(s)} \text{GPA}_i)$$

Utility of dropping out of the platform. Finally,

$$u_{0t}(S_i, \tau) = a_0^{(\tau,t)} + a_1 \mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4} a_2^{(s)} \mathbf{1}[\text{SES}_i = s] + a_3 \text{GPA}_i + \ldots$$
$$\sum_{s=2}^{4} \mathbf{1}[\text{Hs_track}_i = s](a_4^{(s)} + a_5^{(s)} \text{GPA}_i)$$

The value of the outside option may differ across individuals, as a function of both observed characteristics and unobserved type. The intercept is also allowed to vary across rounds, with the shifts of intercepts for the first type and period being normalized to 0.

State transitions. To solve the dynamic model, students take into account the probability to receive an offer $\Pr(j_{t+1} = j' | \Omega_{it})$. We consider a parametric, but flexible re-

[14] The variable Hs_Track_i may take four distinct values, as we distinguish between general, technical, and vocational tracks, and we also allow heterogeneity within the general track along two subtracks (sciences vs humanities and social sciences).

[15] 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.

lationship by estimating a logit model that predicts the probability to improve on the current offer, $\Pr(j_{t+1} \neq j_t|\Omega_{it})$, and a conditional logit among the higher-ranked options $\Pr(j_{t+1} = j'|\Omega_{it}, j_{t+1} \neq j_t)$.

The binary logit includes the student's observed characteristics S_i and type τ and 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 city dummy, rent, the rank and the distance to the current offer, and we add controls for the number of higher-ranked programs in the ROL of each type. For the conditional logit, we first predict a program's selectivity.[16] This index enters with a round-specific effect and interactions with observed characteristics S_i and type τ. Furthermore, we include dummy variables for types and majors, as well as the city dummy, rent, the rank and distance to the offer.

5.3 Estimation

5.3.1 Estimation with Known Types

With known types τ, we need to estimate the utility of being matched to a program $u_j(S_i, \tau)$, the early acceptance advantage $e_j(S_i, \tau)$, the outside option $u_{0t}(S_i, \tau)$ and the waiting costs $\omega(S_i, \tau)$. Moreover, we need to recover the state transitions $\Pr(j_{t+1} = j'|\Omega_{it})$ from the data.

Let θ capture all parameters to estimate. We can then write a likelihood function for the model where each individual's likelihood contribution is given by:

$$L_i(\theta) = L_{1i}^{ROL}(\theta_1) \prod_{t=1}^{3} (L_{it}^{TRANS}(\theta_2) L_{it}^{DDC}(\theta_1, \theta_2, \theta_3))$$

with $\theta = (\theta_1, \theta_2, \theta_3)$. $L_{1i}^{ROL}(\theta_1)$ is given by the probability of the observed ROL (2) and captures the utility parameters of each program up to scale. θ_2 are the parameters governing the state transitions. Finally, $L_{it}^{DDC}(\theta_1, \theta_2, \theta_3)$ is given by the choice probabilities in each round (6) with θ_3 the remaining parameters. These are the scale of the first stage trembling hand error (relative to the scale of utility) σ, the parameters of the early acceptance utility,

[16] To do this, we first estimate a logit on the full sample of applicants from 2015, where the dependent variable is equal to one if the student was admitted in the first round, and compute a program's selectivity index as the associated predicted latent variable. We restrict the estimation sample to the student-program pairs where the student was an actual applicant, i.e. programs ranked weakly above the one from which the student received an offer in the first round. For the production and services majors, we allow for different effects in technical and vocational programs. The Econ./Law, STEM and Humanities majors are allowed to have different effects in prep-school, Bachelor and other programs.

the waiting cost parameters and the dropout parameters.

Note that the loglikelihood function is additively separable with loglikelihood contributions:

$$l_i(\theta) = l_{1i}^{ROL}(\theta_1) + \sum_{t=1}^{3}(l_{it}^{TRANS}(\theta_2) + l_{it}^{DDC}(\theta_1, \theta_2, \theta_3)).$$

Therefore, we can obtain consistent estimates by sequential estimation. We first obtain the estimates of θ_1 from a rank-ordered logit model on the ROLs.[17] We also obtain θ_2 from the (conditional) logit models that predict state transitions. We then use the estimated values of θ_1 and θ_2 to estimate the remaining parameters θ_3 in the dynamic choice model.

CCP estimation. In order to estimate θ_3 using a full solution method, one would need to solve the stage 2 of the model for each value of the state. This is cumbersome as the state space consists of every option that student i included in its ROL.

Dynamics enter through the choices allowing a student to stay on the 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 $k = 2$ as suggested by Hotz & Miller (1993) and Arcidiacono & Miller (2011). In particular, we can rewrite the ex ante value function (7) as a function of the conditional value function of dropout ($k = 3$), a terminal action that is always available, and the Conditional Choice Probability (CCP) of that action:

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

No future value terms appear on the right-hand side because, with a terminal action, the finite dependence property trivially holds (Arcidiacono & Miller (2011)).

We can use this to re-write the conditional value function of $k = 2$:

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

where the last line follows from $\sum_{j' \in \mathcal{R}_i^{j_t} \cup \{j_t\}} \Pr(j_{t+1} = j'|\Omega_{it}) = 1$.

[17] 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 explained by (Train, 2009, page 65). In practice, we sample 450 alternatives out of the total set of 10,150.

Using these conditional value functions, we no longer need to solve the model to estimate the parameters if we estimate CCPs (i.e. $\Pr(d_{it+1}^{DDC} = 4|\Omega_{it}, j_{t+1})$ for $t+1 = 2, 3$) in a first step. The resulting estimator becomes similar to the estimator of static model with a correction term.[18]

5.3.2 Estimation with Unknown Types

Let there be M types τ with probability to occur π_τ. We then obtain the following log-likelihood contributions:

$$l_i(\theta, \pi) = \ln \sum_{\tau=1}^{M} \pi_\tau [l_{1i}^{ROL}(\theta_1) \prod_{t=1}^{3} (l_{it}^{TRANS}(\theta_2) l_{it}^{DDC}(\theta_1, \theta_2, \theta_3))]$$

with an additional vector of parameters to estimate: $\pi = (\pi_2, ..., \pi_M)$ and $\pi_1 = 1 - \sum_{\tau=2}^{M} \pi_\tau$. Note that the log-likelihood function is no longer additively separable, preventing us from estimating the model in stages. Moreover, our estimation approach requires CCPs to depend on types. We address these issues by following the estimation approach of Arcidiacono & Miller (2011). This is an adaptation of the EM algorithm and can be summarized as follows. We first specify the number of types M and provide a set of starting values for θ. We use this to calculate the probability of each observation i to belong to each type τ and the type probabilities π. We then estimate the CCPs and the model as if types are known, using the individual probabilities as weights. The new set of estimates for θ are used to update the types. This is repeated until convergence of the likelihood function. We apply the two-stage estimator of Arcidiacono & Miller (2011) which replaces l_{it}^{DDC} by the prediction of a flexible logit.[19] In an additional step, we then recover the structural parameters using l_{it}^{DDC} and a flexible binary logit for the drop out option only.[20]

[18] We predict CCPs of drop 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 city dummy, rent, the rank of the offer and the selectivity index.

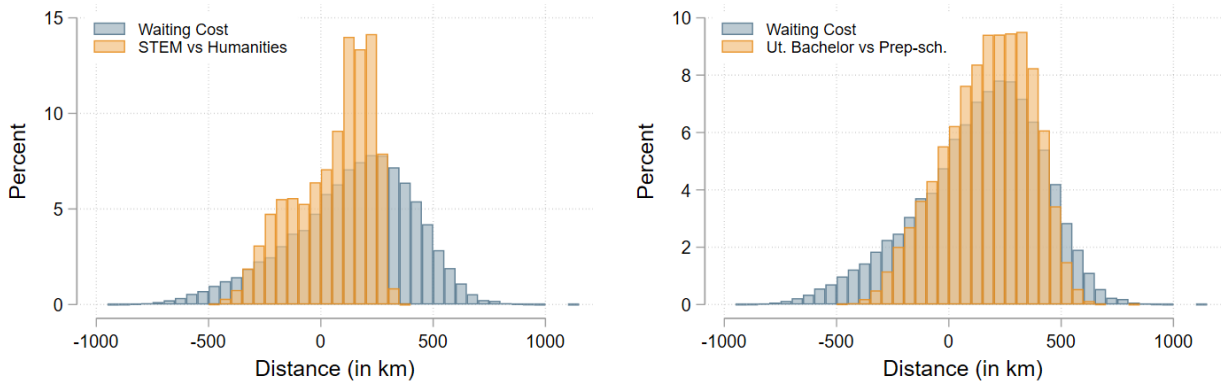
[19] We estimate a multinomial logit on the three options by letting all observable student characteristics S_i and unobserved types τ have choice-specific effects. Moreover, we allow for different intercepts by round.

[20] 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

For brevity, we focus the discussion on waiting costs, which play a central role in our framework, and defer the discussion of utility parameters to Appendix C. Utility and waiting cost parameter estimates are reported in Tables C-1 through C-6. Parameter estimates for the graduation model are shown in Tables C-7 through C-13, while parameters governing the on-platform offer process can be found in Tables C-14 and C-15.

Figure 3: Waiting Costs



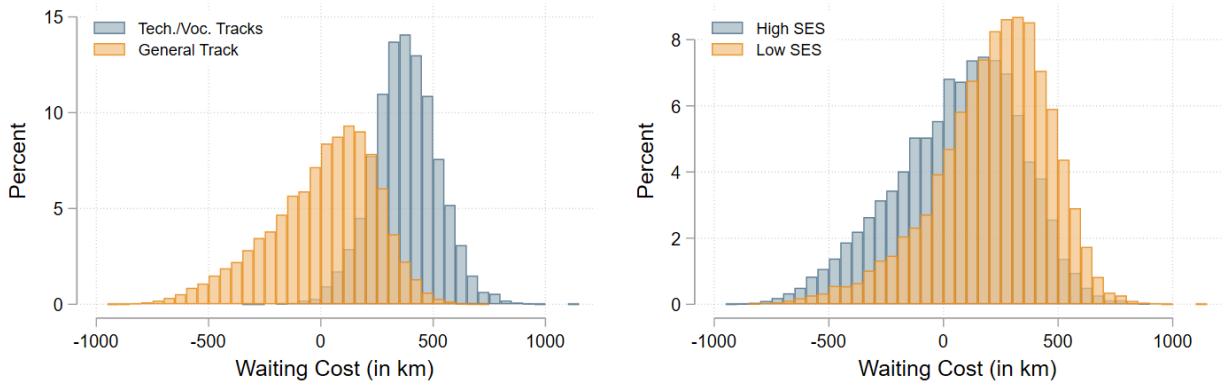
(a) Waiting Costs vs. Preferences over Majors

(b) Waiting Costs vs. Preferences over Types

Notes. This figure shows the distribution of estimated waiting costs for students for whom choosing *delay* is a possibility in Round 1 (that is, those with an offer that is not from their top-ranked program).For reference, Figure C-1 shows the distributions of waiting costs at the end of Round 1 and 2 are relatively similar. Waiting costs are expressed in distance-increase-equivalent (in km). In the top panel, the distribution of waiting costs is compared to the distribution, across students, of average utility differences between STEM programs and humanities programs. In the bottom panel, the distribution of waiting costs is compared to the distribution, across students, of average utility differences between Bachelor programs and prep-school programs.

Waiting costs are substantial and highly heterogeneous across students. Indeed, the median 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 understand 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 by 103 km, and that the average distance between a student's home and their assigned program in 60km (Table A-2). To illustrate the magnitude of waiting costs relative to other aspects of college decisions, we report in Figure 3 the distribution of estimated waiting costs in comparison to the relative valuation of fields of study (top panel) and programs types (bottom panel). The figure reveals that the magnitude of waiting costs is comparable to the utility gains associated with being assigned to a program in a more preferred type (specifically

Figure 4: Heterogeneity in Waiting Costs



(a) Waiting Costs by High-School Track

(b) Waiting Costs by SES

Notes. This figure shows the distribution of estimated waiting costs for students for whom choosing *delay* is a possibility in Round 1 (that is, those with an offer that is not from their top-ranked program). For reference, Figure C-1 shows the distributions of waiting costs at the end of Round 1 and 2 are relatively similar. Waiting costs are expressed in distance-increase-equivalent (in km). In the top panel, the distribution of waiting costs is plotted separately for graduates from the general high-school track and for graduates from the technical and vocational high-school track. In the bottom panel, the distribution of waiting costs is plotted separately for higher-SES students (comprising high- and medium-high SES groups in the data) and lower-SES students (comprising low- and medium-low SES groups in the data).

Bachelor vs. prep school) or field of study (STEM vs. humanities). In other words, for many students, average differences in utility between majors or program types may be offset by the cost of delaying acceptance.

We next explore the heterogeneity of waiting costs across students. Figure 4 shows the distribution of waiting costs conditional on high-school track (top panel) and SES (bottom panel). High-school track is the dimension along which we estimate the largest difference in waiting costs, with a median waiting cost equivalent to a 47km-increase for general-track students, against 374km for technical- and vocational-track students. Turning to SES, the median waiting cost is equivalent to a 246km-increase for lower-SES students against 93km for higher-SES students.

7 The Value of Sequential Admission

We investigate in this section the value of sequential admission mechanism, relative to a more standard one-round mechanism. In order to do so, we conduct a counterfactual exercise based on the application decisions model and the parameter estimates discussed above.

7.1 Implementation

We use a counterfactual exercise to understand how a sequential mechanism affects students' outcomes, in particular graduation rates and welfare. To do so, we compare graduation rates and welfare under the status quo sequential mechanism (SQM), and a more standard one-round mechanism (1RM). Under the 1RM, students submit ROLs and get offers just like they do in the first round of the SQM. In response to these offers, they can only *accept* or *drop out* of the platform, the value of each alternative being given by Eqs. (3) and (5), respectively. For simulations of matches under both mechanisms, we take ROLs and Round-1 offers as given. Under the 1RM, we then draw ϵ_{ikt} shocks for $t = 1$ to determine students' (final) acceptance decisions. Under the SQM, students make their Round-1 decisions based on these $t = 1$ 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-14 and C-15).[21] 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 Eq. (8).

7.2 Results

We now present results showing how a sequential mechanism affects graduation rates and student welfare. Throughout this section, we focus on students who do not receive an offer from their top-ranked program in the first round of the SQM, as they are the only students for whom SQM and 1RM may yield different outcomes.[22]

Effects on offers and acceptance decisions. As a first step, to understand how the SQM affects graduation outcomes relative to the 1RM, and to understand which students are led to graduate by the SQM, it is useful to examine how accepting on-platform offers

[21] The process is assumed to be counterfactual-invariant, which for this counterfactual seems like an natural assumption: it is the same mechanism and the same population as the one generating the data used in estimation.

[22] We exclude high-school graduates who do not participate in the centralized assignment process, and our model assumes participation in the centralized assignment process does not depend on the mechanism used. In addition, the numbers presented here focus on students without a top-rank offer in the sequential mechanism as these are the only students whose outcomes are potentially affected in our model, as they are the only ones able to make a choices at the end of the first offer round of the mechanism. This is, in particular, because our counterfactual analysis is done conditional on the ROLs observed in the data, and therefore, conditional on the offers extended in the first round.

Table 6: Final On-Platform Decision

	Sequential Mechanism			
	Drop Out	Accept		*Total*
One-Round Mechanism				
Drop Out	.08	.10		*.18*
		Same Match	Higher Rank	
Accept	.07	.65	.10	*.82*
Total	*.15*	*.85*		*1.00*

Notes. This table shows the shares of final on-platform decisions among students across the two mechanisms. It focuses on the sample of 23,391 students who do not receive an offer from their top-ranked program in the SQM.

compare across the two mechanisms. Table 6 shows how match outcomes differ by the end of the assignment procedure. In the 1RM, 18% of all applicants do not accept any offer. In the SQM, this number is reduced to 15%. This net three-point decrease results from the combination of two effects. On the one hand, among the 18% of applicants not accepting any offer in the 1RM, 56% (amounting for 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*. On the other hand though, about 9% of applicants who accept a match under the SQM do not under the 1RM (amounting for 7% of all applicants). The "non-monotonic" effect of the SQM on matches is understood by realizing that students do not automatically accept the offers they receive on the platform.[23] The students "losing a match" under the SQM are students who receive the same offer in Round 1 of the SQM as they do in the 1RM but accept their offer in the 1RM while they delay in the SQM, before ultimately dropping out. This seems to be driven by students drawing a high shock for the drop-out option in round 2 or 3. Conversely, note that not all students gaining a match under the SQM do so by gaining an offer. In fact, 66% of them do not receive any offer in the 1RM, while the others do but reject it. In the SQM, they still receive that original offer but delay their decision to wait for another offer and eventually accept a match in the later round. Finally, note that 75% of students accept an offer in both scenarios; 65% accept the same offer under both, while 10% receive and accept a higher-ranked offer under the SQM.

Mechanism 1: extended/broader access under the SQM. The academic trajectories of students who gain a match under SQM are shown in Tables 7. Under SQM, 60% of them

[23]The effect of switching from 1RM to SQM on whether or not students receive offers is monotonic by construction.

Table 7: Graduation Rates Across Mechanisms —Students Gaining 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 shows this distribution of graduation outcomes across mechanisms for students who gain a match under the SQM, that is, students who accept an offer under the SQM, but do not under the 1RM.

eventually graduate from the higher education system. Slightly more than half of these graduates would obtain a degree under the 1RM as well.[24] The rest is led to graduate by the SQM and the fact that they receive a match they would not have obtained under the 1RM. These students represent 65% of the students brought to graduation by the SQM —the rest of the students who graduate under the SQM but not under the 1RM being students who get offers under both 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.

Table 8: Graduation Rates Across Mechanisms —Students Improving their Match

	Sequential Mechanism		
One-Round Mechanism	Do Not Graduate	Graduate	*Total*
Do Not Graduate	.21	.08	*.29*
Graduate	.03	.68	*.71*
Total	*.25*	*.75*	*1.00*

Notes. This table shows this distribution of graduation outcomes across mechanisms for students who improve their match under the SQM, that is, students who accept an offer under both the SQM and the 1RM, but from a higher-ranked alternative in the SQM than under the 1RM.

Mechanism 2: Improved offers under the SQM. As seen in Table 6, 10% of applicants obtain a match in both procedures but eventually accept a higher-ranked offer in the SQM.

[24] i.e., they may enroll in and graduate from an off-platform program, or they may participate in the centralized assignment procedure again in a subsequent year, and eventually graduate from an on-platform program. Note that although they graduate under both mechanisms, they may graduate from different programs across mechanisms. In fact, we find that 41% graduate of them graduate from a program of different type and/or major under each mechanism.

The graduation outcomes of those who receive an improved offer are shown in Table 8. 8% graduate only under the SQM; they represent 28% of the students who graduate under SQM but not under 1RM. Only 3% do not graduate under SQM while they do under 1RM.

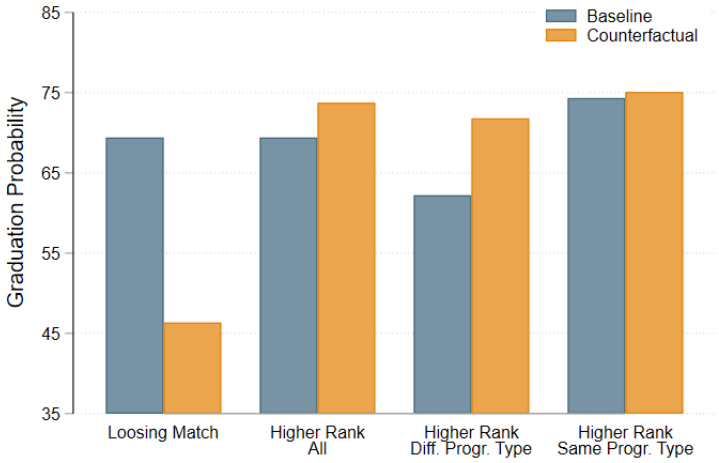
Heterogeneity across students and drivers of graduation outcomes. Table 9 shows the characteristics of students who gain or improve their match, and of those who gain graduation as a consequence. Because vocational and technical high-school students are the most likely to be without an offer at the end of 1RM (Appendix Table D-2), they are also the most likely to gain a match from the SQM, while general-track high-school graduates are more likely to improve their match (see Columns to (4) and (6) vs Column (2) in Table 9). Because low-SES students and scholarship recipients are overrepresented among vocational and technical high-school graduates, we observe that they are more likely to gain a match while medium-SES students tend to improve their match at a higher rate.

Figure 5 sheds light on the mechanisms leading students who gain or improve their match to graduate at higher rates. The first pair of bars illustrates the effect of matching on platform on graduation. The first (orange) bar shows the predicted graduation rate of those matching on platform. The second bar shows the predicted average graduation probability for the same students had they not matched on the platform. Had they not received a match, the graduation rate of these students would have been reduced by 34%.[25] Explaining the heterogeneity observed in Table 9, matching on platform is a much more crucial determinants of post-secondary graduation for students from the vocational and technical high school tracks than it is for general-track students —had they not secured a match, matched vocational- and technical-track students would be 55% less likely to graduate from the higher education system; against 24% for general-track students (Figure D-1 in Appendix).

The second set of bars illustrates the effect on graduation of improving one's on-platform match by one rank. The first bar again shows the average graduation rate of those matching on platform. The second bar 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 same major and type as the baseline match. Figure 5 shows that the graduation gains

[25] Reduction from .70 to .46, that is =.34

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



NOTES. This figure illustrates the role of accepting an on-platform match and of the rank of the accepted match on students' probability to graduate from the higher education system.

following a match improvement are entirely driven by a better match between the program and student characteristics, rather than by a pure rank effect.[26] The effect of matching one-rank higher on graduation probability is about twice larger for matched vocational- and technical-track students than it is for general-track students (8 vs 3.6 percent increases, respectively, in Figure D-1).

Overall effect on graduation. Table 10 shows how graduation rates of applicants compare across the two mechanisms: the graduation rate of students without a top-ranked offer is higher by two percentage points (or 5.9%) under the SQM than under the 1RM. This is a non-negligible effect. For comparison purpose, in recent work investigating the role of off-platform options in Chile, Kapor et al. (2024) found that removing universities which joined the platform would result in around a third of percentage point decrease in graduation rates.

Welfare effects. Table 11 shows average changes in welfare from 1RM to SQM for students as a function of their match outcomes under both mechanisms. We focus on welfare

[26] This isn't 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 and offer from a program with different type and/or major in the SQM as compared to 1RM (Appendix Table D-1).

Table 9: Student Characteristics

	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	0.497	0.505	0.471	0.508	0.497
High SES	0.329	0.347	0.354	0.285	0.253	0.332	0.292
Med-high SES	0.160	0.153	0.154	0.154	0.143	0.157	0.138
Med-low SES	0.292	0.281	0.284	0.316	0.344	0.306	0.272
Low SES	0.220	0.219	0.208	0.246	0.260	0.205	0.297
Scholarship Recip.	0.166	0.167	0.156	0.169	0.162	0.166	0.226
High-school Track							
General	0.667	0.627	0.651	0.485	0.427	0.707	0.538
Technical	0.218	0.238	0.221	0.278	0.294	0.209	0.364
Vocational	0.115	0.135	0.127	0.236	0.279	0.083	0.097
High-School GPA							
General Track	0.139	0.142	0.142	-0.251	-0.371	0.145	-0.247
	(.975)	’(.977)	(.991)	(.886)	(.74)	(.929)	(.843)
Technical Track	-0.044	-0.252	-0.252	-0.402	-0.423	-0.104	-0.359
	(.815)	’(.741)	(.73)	(.714)	(.75)	(.67)	(.872)
Vocational Track	0.536	0.405	0.405	0.299	0.292	0.683	0.900
	(.775)	’(.761)	(.783)	(.837)	(.711)	(.698)	(.865)
Unobserved Type							
Type 2	0.501	0.498	0.482	0.499	0.514	0.446	0.369

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.

Table 10: Graduation Rates Across Assignment Mechanisms

	Sequential Mechanism		
	Do Not Graduate	Graduate	*Total*
One-Round Mechanism			
Do Not Graduate	.32	.04	*.36*
Graduate	.02	.62	*.64*
Total	*.34*	*.66*	*1.00*

Notes. This table shows this distribution of graduation outcomes across mechanisms for students with no top-ranked offer in the first round of the SQM.

from the point of view of the end of Round 1 (in SQM), that is, of the end of the assignment procedure in 1RM. At that point in time, students have made their decision for the round. Under 1RM, they get to consume the flow utility associated with that decision. Under SQM, students for whom the procedure ends at the end of round 1 (because they accept their offer or drop out of the platform) also get to consume flow utility associated with their decision; while students who choose *delay* also receive the option value associated with continuing to the next round, net of waiting costs. Under this definition of welfare, a student who make the same decision at the end of Round 1 in both mechanisms (that is, accepting the offer received or dropping out of the platform) does not experience any welfare change from one mechanism to the other. We highlight two key results from Table 11. First, average welfare changes are positive for all pairs of potential match outcomes. As a reference to interpret magnitudes in Table 11, note that the average difference in utility between students' first and second-ranked program is equivalent to a reduction in the home-university distance by 103 km, and that the average distance between a student's home and their assigned program in 60 km (Table A-2). Second, average welfare gains are about two to three times higher for students with potential match outcomes that differ across mechanisms than for students whose potential outcomes are the same. To understand these facts, recall that only students who choose *delay* at the end of Round 1 in SQM will experience a change in welfare relative to SQM. Naturally, only students with a positive continuation value net of waiting costs choose *delay* at the end of Round 1. In addition, note that only those who choose delay may in the end obtain a different match outcome under SQM relative to 1RM. This directly explain our two results. Average welfare gains are much larger for students with match outcomes that differ under the two mechanisms that for students for whom these match are the same because in the former group, all students decided to wait at the end of Round 1 of the SQM and got to enjoy the continuation value. Only a fraction of those with match outcomes that coincide under both mechanisms chose to wait —47% of those who drop out of the platform without a match under both mechanisms delay in Round 1 of SQM; 42% of those who accept the same offer in both mechanisms do so.[27] Table 11 is a neat illustration of the value to students of being allowed to delay their decision and wait for better offers.

[27]This reasoning also explains why students who accept a match under 1RM but do not, and drop out of the platform under SQM enjoy much larger welfare under SQM than under 1RM. These students receive the same offer in the first round of SQM as they do in 1RM. While they accept it in 1RM they all reveal that they are better off delaying their decision under SQM, before, in later rounds, preferring to drop out of the platform over accepting the offer they held on to.

Table 11: Welfare Effects by Match Outcome

	Sequential Mechanism			
	Drop Out	Accept		All
One-Round Mechanism				
Drop Out	478	1,703		1,183
Share delaying in Round 1	*.47*	*1.00*		*.77*
		Same Match	Higher Rank	
Accept	1,405	603	1,513	788
Share delaying in Round 1	*1.00*	*.42*	*1.00*	*.55*
Total	938	846		860
Share delaying in Round 1	*.73*	*.56*		*.59*

Notes. This table shows welfare effects, expressed distance-reduction equivalent (in km), as a function of potential match outcomes in each mechanism. The table also shows, in italics, the share of students in the potential-match-outcome cell who chose *delay* at the end of Round 1 of the SQM. As a reference, the average difference in utility between students' first and second-ranked program is equivalent to a reduction in the home-university distance by 103 km, and the average distance between a student's home and their assigned program in 60 km (Table A-2)

As Table 11 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 what don't they do so? Among students with no top-ranked offer in Round 1, 42% choose not to delay.[28] Comparing Column (3) to Column (2) in Table 9 shows that high-school track, scholarship eligibility, and unobserved type are the main dimensions along which selection into delaying is determined. As compared to the average student who does not get a top-ranked offer in the first round of the SQM, students who choose *delay* in this first round are 7% less likely to be scholarship recipients (and 2% more likely to be high-SES); seven and six percent less likely to be from the technical and vocational high-school tracks, respectively; and 3% less likely to be of unobserved type 2.[29] Estimates suggest that this heterogeneity in the choice of whether or not to delay is driven by heterogeneity in waiting costs, rather than in the option value of waiting. Indeed, on the one hand, waiting-cost estimates are directly consistent with our finding that students from the vocational and technical high school tracks are those least likely to delay. Appendix Table C-6 shows that waiting costs are particularly

[28] 53% of those with no match in either mechanism (Table 11), that is, 53% of 8% of the the population of applicants with no top-ranked offer (Table 6). 58% of those with same match in either mechanism (Table 11), that is, 58% of 65% of the population of applicants with no top-ranked offer (Table 6). Hence, a total share of $.53 \times .08 + .58 \times .65 = .42$.

[29] Percentages changes obtained from Table 9 as $(.156 - .167)/.167 = -7\%; (.354 - .347)/.347 = 2\%; (.221 - .238)/.238 = -7\%; (.127 - .135)/.135 = -6\%;$ and $(.482 - .498)/.498 = 3\%$.

high for these students. Scholarship eligibility is, to a lower extent, also associated with higher waiting costs; unobserved type, however, does not seem to be. On the other hand, our estimates suggest there is little difference in the option value of waiting across groups. Heterogeneity in continuation value could be due to heterogeneity in the probability to get an offer in a later round, and heterogeneity in the rank of the first-round offer —intuitively, holding everything else constant, a student with more programs ranked ahead of first-round offer may have a higher probability to get an new offer as there are more programs he could get an offer from. Appendix Tables D-3 and D-2 show, respectively, that there is no significant differences in the average probability to get a later-round offer or in the average rank of the first-round offers received across students from different high-school tracks, or with different scholarship eligibility status or unobserved type.

8 Concluding Remarks

In this paper we investigate the consequences of using a sequential rather than a single-round centralized college admission mechanism. We focus on the context of the French APB admission mechanism, where students are allocated to higher education programs based on a sequential admission process with up to three offer rounds. We develop a parsimonious dynamic model of application and acceptance decisions, which captures a key dynamic trade-off between receiving a potentially better offer in the next round, and the disutility of waiting before enrolling in a program. We find that a multi-round system entails large welfare gains. These effects are driven by the subgroup of students who do not receive their first-ranked alternative in Round 1, and attach a potentially large value to the option of waiting for a (better) match. We also document the existence of large waiting costs, resulting in sub-optimal matches, particularly so for low-SES students. From a policy perspective, our findings point to the importance of reducing these cost by limiting the time needed to run the mechanism, and possibly also by facilitating access to local housing markets.

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A Institutional Background and Data

A.1 Institutional Background: Additional Details

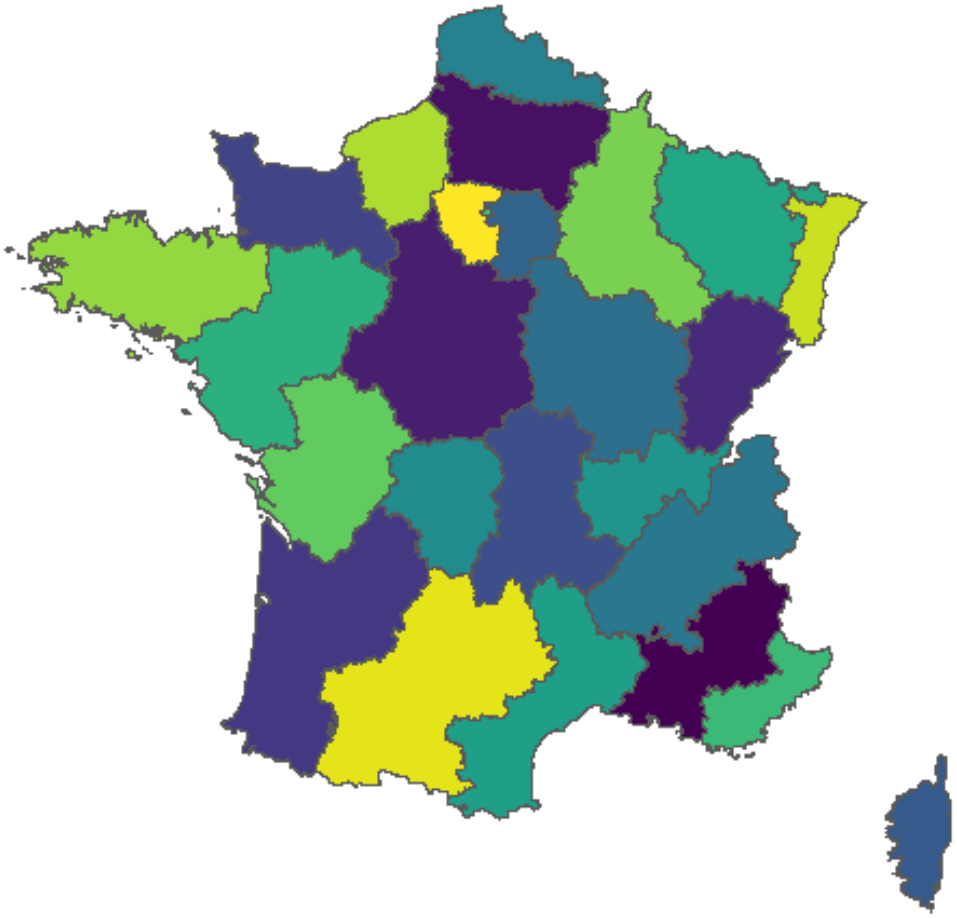
Secondary Education in France Primary, secondary, and higher education in France are centralized and regulated by the Ministry of Education. The curriculum taught is the same across all schools, and there is no formal tracking of students until the beginning of high school (ninth to twelfth grades), when students make two decisions. First, they choose their *track* among three (*general*, *technological* or *vocational*). Second, within each track, students choose a *high-school major*, which will determine their exact high-school curriculum. In the empirical analysis we will distinguish between four tracks, by distinguishing between a general track with a major in sciences and a general track with a major in humanities or social sciences. At the end of twelfth grade, students take a national exam (*Baccalauréat*). The content of the exam is determined by students' choice of track and high-school major, and obtaining a passing grade is necessary to graduate high-school and be eligible to enter higher education. Figure A-1 shows the regions used by Bachelor programs to determine coarse priority groups.

Catchment Areas The country is partitioned into 30 catchment areas, called *Académies* (Figure A-1). Each of them is responsible for organizing and administering educational policies within its area, following the directives of 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, which consists in four categories in the data: High (company managers, executives, liberal professions, engineers, intellectual occupations, arts professions), Medium-High (technicians and associate professionals), Medium-Low (farmers, craft and trades workers, service and sales workers), 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 out of 20 points. A four-category discrete measure of this exam score is reported in our college-application data: highest honors (score above 16 out of 20); high honors (score between 14

Figure A-1: Academic regions in France



and 16 out of 20)l honors (12–14), and pass (10–12). Note that 10 out of 20 is the minimum score required to pass the end-of-high school exam, graduate from high school, and access post-secondary education. All students in our sample are eligible to enter post-secondary education.

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

Cost of housing Measures of local rents for 99 cities in France are taken from: https://www.century21.fr/pdf/logement_etudiant/2015/logement_etudiant_2015.pdf.

Off-Platform Programs We take advantage of the unique opportunity to track students in the higher education market, regardless whether they enroll on- or off-platform, thanks to the census gathering all students enrolled in higher education in France (SISE).

Thanks to this dataset, we can also quantify the share of students enrolling off-platform in France. Whether a program is on- or off-platform is not directly indicated in the census dataset, while program identifiers are not defined at the same level as those used in the centralized allocation procedure. To be able to quantify the share of off-platform programs, we use the following strategy. We define a program in SISE as an institution-diploma pair, and complete this information with the number of nursing programs and students enrolled there. There are 8,040 programs in 2015, with a total of 374,964 students enrolled. We then merge these latter dataset to the APB dataset using the student identifier and generate the share students enrolled in a SISE program who are accepting an offer in APB.[30] We then define a SISE program as being on-platform if at least a third of the enrolled students are found to be accepting an offer on the platform. Note that this share is not 100% as we make some sample restrictions in APB (such as non-missing high-school grades) which cannot be made in SISE, explaining that for some on-platform programs we would find that there are more enrolled students than students accepting an offer on the platform. We also allow for some students to renege their accepted offer on APB at the start of the academic year, implying that a small share of students accepting an offer on APB are enrolled in an off-platform program. Following this procedure, we find that 13.3% of the first-year higher education programs in France are off-platform, and they enroll 11.8% of the students.

Sample description

[30]Note that SISE programs are more aggregated than APB programs. Thus, we would not have that students enrolled in the same SISE program all accept an offer from the same program in APB.

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	
General	0.61
Technical	0.22
Vocational	0.16
General High-school Track - Major	
Sciences	0.54
Social Sciences	0.31
Humanities	0.15
High-School GPA	
General 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	59.89
Urban location (Main city)	0.64
Monthly rent (cond. on urban location)	458.89
Observations	426,799

Notes. This table describes the characteristics of applicants and their final assignment. Unless othewise specified, numbers provided are sample shares. See Appendix A.2 for details about the definition of socio-economic categories and the construction of average rent.

B Parameterization

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

$$v_{i1t} = u_j(S_i, \tau) + w_j^{(t)}(S_i, \tau)$$

with $w_j^{(t)}(S_i, \tau)$ 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 $w_j^{(t)}$:

$$\begin{aligned}
w_j^{(t)}(S_i,\tau) = &\sum_k \mathbf{1}[\text{Prog_Type}_j = k] \cdot \Big(b_0^{(k,\tau,t)} + b_1^{(k,t)}\mathbf{1}[\text{female}_i] + \sum_{s=2}^{4} b_2^{(k,s,t)}\mathbf{1}[\text{SES}_i = s]\Big) \\
&+ \sum_k \mathbf{1}[\text{Field_Study}_j = k]\Big(b_3^{(k,\tau,t)} + b_4^{(k,t)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4} b_5^{(k,s,t)}\mathbf{1}[\text{SES}_i = s]\Big) \\
&+ b_6^{(t)}\text{Distance}_{ij} \\
&+ \mathbf{1}[\text{Same_Catchment}_{ij}] \cdot \Big(b_7^{(k,\tau,t)} + b_8^{(k,t)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4} b_9^{(k,s,t)}\mathbf{1}[\text{SES}_i = s] + \\
&\qquad \text{GPA}_i(b_{10}^{(k,t)} + \sum_{s=2}^{4} b_{11}^{(k,s,t)}\mathbf{1}[\text{Hs_Track}_i = s])\Big) \\
&+ \mathbf{1}[\text{Paris}_j] \cdot \Big(b_{12}^{(k,\tau,t)} + b_{13}^{(k,t)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4} b_{14}^{(k,s,t)}\mathbf{1}[\text{SES}_i = s] + \\
&\qquad \text{GPA}_i(b_{15}^{(k,t)} + \sum_{s=2}^{4} b_{16}^{(k,s,t)}\mathbf{1}[\text{Hs_Track}_i = s])\Big) \\
&+ \mathbf{1}[\text{Main_City}_j] \cdot \Big(b_{17}^{(k,\tau,t)} + b_{18}^{(k,t)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4} b_{19}^{(k,s,t)}\mathbf{1}[\text{SES}_i = s] + \\
&\qquad \text{GPA}_i(b_{20}^{(k,t)} + \sum_{s=2}^{4} b_{21}^{(k,s,t)}\mathbf{1}[\text{Hs_Track}_i = s])\Big) \\
&+ \text{Rent}_j \cdot \Big(b_{22}^{(k,\tau,t)} + b_{23}^{(k,t)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4} b_{24}^{(k,s,t)}\mathbf{1}[\text{SES}_i = s] + \\
&\qquad \text{GPA}_i(b_{25}^{(k,t)} + \sum_{s=2}^{4} b_{26}^{(k,s,t)}\mathbf{1}[\text{Hs_Track}_i = s])\Big)
\end{aligned} \tag{B-1}$$

where all variables are defined in Section 5.2

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

$$
\begin{aligned}
h_m(S_i,\tau,j) = \sum_k \mathbf{1}[\text{Prog_Type}_m = k] \cdot \Big(\kappa_0^{(k,\tau)} + \kappa_1^{(k)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4}\kappa_2^{(k,s)}\mathbf{1}[\text{SES}_i = s] + \kappa_3^{(k)}\mathbf{1}[\text{Scholarship}_i] + \dots \\
\kappa_4^{(k)}\text{GPA}_i + \sum_{s=2}^{4}\mathbf{1}[\text{Hs_Track}_i = s](\kappa_5^{(k,s)} + \kappa_6^{(k,s)}\text{GPA}_i)\Big) \\
+ \sum_k \mathbf{1}[\text{Field_Study}_m = k]\Big(\kappa_7^{(k,\tau)} + \kappa_8^{(k)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4}\kappa_9^{(k,s)}\mathbf{1}[\text{SES}_i = s] + \kappa_{10}^{(k)}\mathbf{1}[\text{Scholarship}_i] + \dots \\
\kappa_{11}^{(k)}\text{GPA}_i + \sum_{s=2}^{4}\mathbf{1}[\text{Hs_Track}_i = s](\kappa_{12}^{(k,s)} + \kappa_{13}^{(k,s)}\text{GPA}_i)\Big) \\
+ \mathbf{1}[m = j]\Big(\kappa_{14} + \sum_k \kappa_{15}^{(k)}\mathbf{1}[\text{Rank}_{ij} = k]\Big) \\
+ \sum_k \kappa_{16}^{(k)}\mathbf{1}[\text{Prog_Type}_m = \text{Prog_Type}_j = k] + \sum_k \kappa_{17}^{(k)}\mathbf{1}[\text{Field_Study}_m = \text{Field_Study}_j = k] \\
+ \sum_k \mathbf{1}[\text{Rank}_{ij} = k]\Big(\kappa_{18}^{(k)}\mathbf{1}[\text{Female}_i] + \sum_{s=2}^{4}\kappa_{19}^{(k,s)}\mathbf{1}[\text{SES}_i = s] + \kappa_{20}^{(k)}\text{GPA}_i \\
\sum_{s=2}^{4}\mathbf{1}[\text{Hs_Track}_i = s](\kappa_{21}^{(k,s)} + \kappa_{22}^{(k,s)}\text{GPA}_i) + \cdots \\
\sum_k \kappa_{23}^{(k)}\mathbf{1}[\text{Field_Study}_m = k] + \sum_k \kappa_{24}^{(k)}\mathbf{1}[\text{Prog_Type}_m = k]\Big)
\end{aligned}
\tag{B-2}
$$

where Rank_{ij} is a the rank of program j in i's ROL which can take the values 1, 2, 3, 4, and "5 or above". rank is 1 to 5+. The variable Field_Study_j denotes the major of program j and can take five distinct values —STEM, Econ./Law, Humanities, Production, and Services. We consider five types of programs one can enroll in after high school — Bachelor program, vocational, technical, two-year prep school, and other. Two-year prep school programs do not deliver degrees, they prepare students to take the entry exam of elite engineering and business schools. Hence, we consider five types of programs one may graduate from —Bachelor program, vocational, technical, elite, and other. With a slight abuse of notation, we use the variable Prog_Type to denote both the type of programs on may enroll in after high-school (j) and the type of programs from which students may eventually obtain a degree (m), and if j is a two-year prep school and m is an elite program, we consider that $\text{Prog_Type}_m = \text{Prog_Type}_j$.

C Estimation Results

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

Parameter estimates for program utility at the time of submitting the ROL are reported in Tables C-1, C-2, and C-3.[31] To interpret estimates correctly, note that they are rescaled using (divided by) the scale parameter σ. To compare them to other estimates (Tables C-4, C-5, and C-6), they need to be multiplied by the estimated value $\hat{\sigma} = 0.098$. This estimate implies that the standard deviation of the "trembling hand" error in the ROL is quite small as it amounts to about 10% of a standard deviation in the taste shocks that enter the dynamic choice model. The utility parametrization (11) involves several indicator variables; *Bachelor program* and *STEM* and *Production* serve as benchmark categories for programs type and field of study.[32] Heterogeneity in preferences across individual characteristics is expressed relative to a benchmark group of high-SES, male students who are not eligible to a scholarship, who graduated high-school in the general track in a humanities or social science major, and with unobservable type 1.

The first part of Table C-1 shows preference estimates for program types, majors, and program location for the benchmark group. The negative coefficient on distance, as well as in the positive nonlinear effects coming from staying in the catchment of residence show that students value proximity to home. The distance parameter can be used to quantify students' preferences for the other program characteristics, noting that distance is expressed in 100 km. Regarding program types, we find that Bachelor programs are on average preferred to other types of programs by the benchmark group with GPA equal to the mean. As GPA increases, other programs become more desirable. For example, for a mean-GPA student in the benchmark group, the difference in utility between a prep-school program and a Bachelor program, with all other things equal, is, on average, equivalent to increase in distance by 190km.[33]. On the contrary, for a student in the benchmark group with a GPA a standard

[31] Standard errors in this version of the draft do not correct for the uncertainty in estimating unobserved types and the use of predicted values for CCPs and state transitions. The estimates of state transitions and the CCP are available upon request.

[32] Note that we have two benchmarks for majors as technical and vocational types do not have STEM, while the others do not have Production.

[33] Distance equivalents in this section are computed as follows: $100 \times (-1.980/1.040) = -190$; $100 \times ((-1.980 + 1 \times 1.680)/1.040) = -29$; $100 \times (-.687/1.040) = -66$; $100 \times ((-.687 + .350)/1.040) - 32$; $100 \times$

Table C-1: Program utility (part 1 of 3)

Common component		
Program type (Benchmark = Bachelor)		
Prep-sch.	-1.980	(0.067)
Tech. prog.	-0.687	(0.097)
Voc. prog.	-3.582	(0.102)
Other prog.	-2.560	(0.094)
Program major (Benchmark = STEM)		
EconLaw	4.360	(0.083)
Human	1.146	(0.081)
Services	4.458	(0.095)
Distance	-1.040	(0.008)
Same catchment area	1.770	(0.023)
Paris	0.277	(0.044)
Main City	-0.290	(0.065)
Main City X same catchment	0.779	(0.072)
Rent	0.179	(0.014)
Rent X same catchment	-0.219	(0.015)
Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High X Prep-sch.	-0.312	(0.067)
Medium-High X Tech. prog.	0.021	(0.074)
Medium-High X Voc. prog.	0.031	(0.079)
Medium-High X Other	-0.166	(0.073)
Medium-Low X Prep-sch.	-0.593	(0.059)
Medium-Low X Tech. prog.	-0.361	(0.066)
Medium-Low X Voc. prog.	-0.253	(0.069)
Medium-Low X Other	-0.757	(0.066)
Low X Prep-sch.	-0.600	(0.072)
Low X Tech. prog.	-0.566	(0.075)
Low X Voc. prog.	-0.239	(0.076)
Low X Other	-0.721	(0.076)
Medium-High X EconLaw	-0.579	(0.077)
Medium-High X Human	0.002	(0.068)
Medium-High X Services	-0.256	(0.074)
Medium-Low X EconLaw	-0.461	(0.067)
Medium-Low X Human	-0.220	(0.060)
Medium-Low X Services	0.257	(0.065)
Low X EconLaw	-0.477	(0.077)
Low X Human	-0.208	(0.068)
Low X Services	0.314	(0.071)

Standard errors in parentheses.

Table C-2: Program utility (part 2 of 3)

Heterogeneity (continued)		
High School Program (Benchmark = General Track - Humanities & Social Sciences)		
General Track - Sciences X Prep-sch.	0.439	(0.065)
General Track - Sciences X Tech. prog.	-0.171	(0.083)
General Track - Sciences X Voc. prog.	-0.376	(0.096)
General Track - Sciences X Other	0.912	(0.072)
Technological Track X Prep-sch.	-0.945	(0.107)
Technological Track X Tech. prog.	0.350	(0.091)
Technological Track X Voc. prog.	1.993	(0.094)
Technological Track - Sciences X Other	0.275	(0.087)
Vocational Track X Prep-sch.	-0.945	(0.107)
Vocational Track X Tech. prog.	-0.045	(0.136)
Vocational Track X Voc. prog.	3.774	(0.116)
Vocational Track - Sciences X Other	1.017	(0.120)
General Track - Sciences X EconLaw	-4.463	(0.079)
General Track - Sciences X Human	-3.911	(0.066)
General Track - Sciences X Services	-4.270	(0.088)
Technological Track X EconLaw	-2.372	(0.090)
Technological Track X Human	-2.812	(0.077)
Technological Track X Services	-1.428	(0.085)
Vocational Track X EconLaw	-2.372	(0.090)
Vocational Track X Human	-1.719	(0.104)
Vocational Track X Services	-1.715	(0.098)
GPA (Benchmark = General Track - Humanities & Social Sciences)		
GPA X Prep-sch.	1.608	(0.046)
GPA X Tech. prog.	0.909	(0.077)
GPA X Voc. prog.	0.441	(0.082)
GPA X Other	0.717	(0.061)
General Track - Sciences X GPA X Prep-sch.	-0.193	(0.057)
General Track - Sciences X GPA X Tech. prog.	-1.066	(0.086)
General Track - Sciences X GPA X Voc. prog.	-0.927	(0.102)
General Track - Sciences X GPA X Other	-0.129	(0.071)
Technological Track X GPA X Prep-sch.	-0.463	(0.100)
Technological Track X GPA X Tech. prog.	-0.508	(0.098)
Technological Track X GPA X Voc. prog.	-0.418	(0.100)
Technological Track X GPA X Other	-0.196	(0.093)
Vocational Track X GPA X Prep-sch.	-0.463	(0.100)
Vocational Track X GPA X Tech. prog.	0.161	(0.151)
Vocational Track X GPA X Voc. prog.	0.486	(0.126)
Vocational Track X GPA X Other	0.313	(0.130)
GPA X EconLaw	4.360	(0.083)
GPA X Human	0.785	(0.056)
GPA X Services	4.458	(0.095)
General Track - Sciences GPA X EconLaw	-0.793	(0.072)
General Track - Sciences GPA X Human	-0.982	(0.066)
General Track - Sciences GPA X Services	-0.400	(0.090)
Technological Track X EconLaw	-0.848	(0.097)
Technological Track X Human	-0.883	(0.083)
Technological Track X Services	0.147	(0.090)
Vocational Track X GPA X EconLaw	-0.848	(0.097)
Vocational Track X GPA X Human	-0.537	(0.115)
Vocational Track X GPA X Services	0.149	(0.103)

Standard errors in parentheses.

Table C-3: Program utility (part 3 of 3)

Heterogeneity (continued)		
Scholarship Status (Benchmark = Without Scholarship)		
With Scholarship X Prep-sch.	-0.172	(0.075)
With Scholarship X Tech. prog.	-0.242	(0.073)
With Scholarship X Voc. prog.	-0.420	(0.073)
With Scholarship X Other	-0.177	(0.076)
With Scholarship X EconLaw	-0.022	(0.077)
With Scholarship X Human	-0.186	(0.066)
With Scholarship X Services	0.123	(0.067)
Sex (Benchmark = Male)		
Female X Prep-sch.	-0.732	(0.047)
Female X Tech. prog.	-1.501	(0.053)
Female X Voc. prog.	-1.353	(0.054)
Female X Other	-0.991	(0.052)
Female X EconLaw	0.566	(0.052)
Female X Human	0.982	(0.047)
Female X Services	1.959	(0.052)
Unobserved Type (Benchmark = Type 1)		
Type 2 X Prep-sch.	1.928	(0.048)
Type 2 X Tech. prog.	1.951	(0.063)
Type 2 X Voc. prog.	1.929	(0.067)
Type 2 X Other	3.141	(0.067)
Type 2 X EconLaw	-3.982	(0.075)
Type 2 X Human	0.485	(0.054)
Type 2 X Services	-5.481	(0.068)

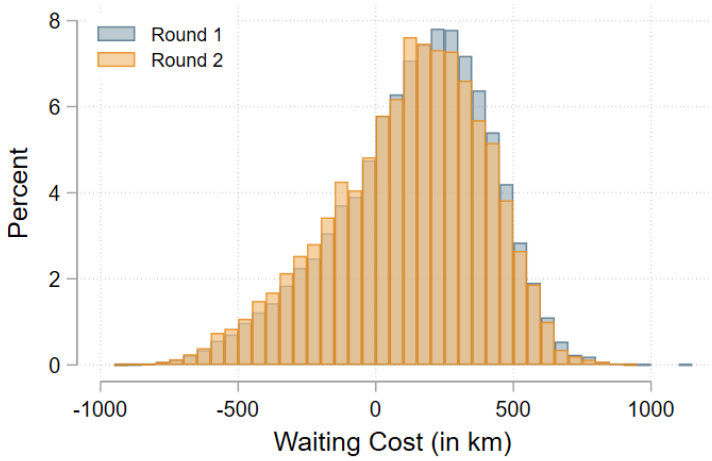
Standard errors in parentheses.

deviation above the mean this difference is equivalent to increase in distance by only 29km. Benchmark-group students (who are from the general high-school track) prefer Bachelor programs over technical and vocational programs, with the difference in utility equivalent to an increase in distance to home by 66 and 344km, respectively. On the contrary, students from vocational high-school track on average prefer vocational post-secondary programs relative to Bachelor programs (equiv. to a 18km-decrease). Students from the technical high-school track also have a lower disutility for technical and vocational post-secondary programs relative to Bachelor program than general-track students (equivalent to a 32km- and 152-km increases, respectively). Findings regarding fields of study are also consistent with intuition. Benchmark group students, who graduated from the general high-school track with a major in humanities or social sciences prefer post-secondary programs in humanities and econ/law over STEM (equivalent to a decrease in distance to home by 110 and 419 km, respectively). On the contrary, students who graduated from the general high-school track with a major in science have a lower preference for post-secondary programs in humanities relative to STEM (by an equivalent of a *in*crease in distance to home by 266 km). They also have a much less strong preference for econ/law over STEM than the benchmark students do (equivalent to a decrease in distance to home by 43 km). Female students also have a stronger preference for non-STEM fields over STEM fields relative to benchmark students, who are men (equivalent to a 152km-decrease for humanities relative to STEM, and to a 514km-decrease for social sciences relative to STEM). Lower-SES students generally have stronger preference for Bachelor programs over all other types of programs than benchmark students, who are high-SES, do. Finally, Table C-3 shows that students of unobservable type 2 are characterized by strong preferences for non-Bachelor programs. We find that 53% of the sample is estimated to be of unobserved type 2. The magnitude of these estimates show the importance of allowing for unobserved heterogeneity in preferences for post-secondary programs.

Turning to the dynamic stage of the model, Tables C-4 and C-5 shows estimates for parameters capturing changes in preferences across rounds of the mechanism (w_j^t in Eq. (3)). Estimates for waiting costs and for the utility of dropping out of the platform are shown in Table C-6. Note that the tables report the negative of the waiting costs parameters so they should be interpreted as utility. The magnitude of and heterogeneity in waiting costs being

$(-3.582/1.040) = -344km$; $= 100 \times ((-3.582 + 3.774)/1.040) = +18$; $100 \times ((-3.582 + 1.993)/1.040) = -152$; $100 \times (1.146/1.040) = +110$; $100 \times ((1.146 - 3.911)/1.040) = -266$; $100 \times (4.360/1.040) = +419$; $100 \times ((4.360 - 3.911)/1.040) = 43$; $100 \times ((1.146 + .437)/1.040) = +152$; $100 \times ((4.360 + .989)/1.040) = +514$.

Figure C-1: Distribution of Waiting Costs across Rounds



NOTES. This figure shows the distribution of estimated waiting costs for students for whom choosing *delay* is a possibility (that is, those with an offer that is not from their top-ranked program), separately for each round. Waiting costs are expressed in distance-increase-equivalent (in km).

discussed in the main text, we focus here on the other parameters.

Benchmark-group students experience, on average, a disutility from using the drop out option. This disutility is lower when the drop out occurs in Round 3 relative to Rounds 1 and 2. Graduates from technical and vocational high school have lower disutility from dropping out of the platform than general-track students. The disutility from dropping out gets larger as GPA increases. Lower SES students, scholarship recipients, and type-2 students experience, on average, larger utility from dropping out than benchmark-group students do.

Table C-4: Utility from accepting (1 of 2)

	Round 1		Round 2		Round 3	
Program type (Benchmark = Bachelor)						
Prep-sch.	2.388	(0.311)	2.345	(0.376)	1.794	(0.424)
× Medium-High SES	0.277	(0.203)	0.181	(0.233)	0.062	(0.370)
× Medium-Low SES	-0.127	(0.200)	0.064	(0.240)	-0.246	(0.374)
× Low SES	-0.027	(0.255)	0.085	(0.272)	-0.307	(0.490)
× Female	0.089	(0.145)	0.087	(0.175)	-0.094	(0.227)
Tech. prog.	1.035	(0.228)	0.125	(0.471)	1.096	(0.553)
× Medium-High SES	0.391	(0.252)	0.495	(0.290)	0.368	(0.408)
× Medium-Low SES	0.053	(0.169)	0.097	(0.218)	0.288	(0.294)
× Low SES	0.353	(0.202)	0.346	(0.306)	0.000	(0.360)
× Female	0.482	(0.182)	0.725	(0.193)	0.458	(0.286)
Voc. prog.	0.793	(0.214)	0.485	(0.416)	1.028	(0.584)
× Medium-High SES	0.224	(0.179)	0.041	(0.247)	0.237	(0.263)
× Medium-Low SES	-0.053	(0.147)	-0.040	(0.228)	0.354	(0.303)
× Low SES	-0.030	(0.139)	-0.163	(0.199)	0.053	(0.311)
× Female	0.500	(0.162)	0.249	(0.193)	0.402	(0.267)
Other prog.	1.231	(0.241)	0.530	(0.329)	1.139	(0.498)
× Medium-High SES	-0.005	(0.232)	0.194	(0.302)	0.088	(0.473)
× Medium-Low SES	-0.214	(0.208)	0.180	(0.282)	0.230	(0.405)
× Low SES	-0.134	(0.188)	-0.145	(0.310)	-0.266	(0.508)
× Female	0.414	(0.166)	0.284	(0.247)	0.146	(0.370)
Program major (Benchmark = STEM)						
EconLaw	-0.460	(0.167)	-1.243	(0.226)	-0.586	(0.219)
× Medium-High SES	0.294	(0.138)	0.048	(0.218)	0.009	(0.226)
× Medium-Low SES	0.272	(0.114)	0.086	(0.195)	0.124	(0.201)
× Low SES	0.448	(0.133)	0.229	(0.217)	-0.032	(0.215)
× Female	0.444	(0.089)	0.598	(0.162)	0.461	(0.169)
Human	-0.323	(0.132)	-1.174	(0.169)	0.052	(0.181)
× Medium-High SES	0.187	(0.132)	0.091	(0.202)	-0.177	(0.221)
× Medium-Low SES	0.210	(0.101)	0.209	(0.168)	0.013	(0.187)
× Low SES	0.408	(0.107)	0.345	(0.168)	0.101	(0.250)
× Female	0.103	(0.083)	0.534	(0.121)	0.219	(0.168)
Services	-0.519	(0.222)	-0.687	(0.429)	-0.110	(0.539)
× Medium-High SES	0.001	(0.170)	0.165	(0.239)	-0.477	(0.299)
× Medium-Low SES	0.132	(0.146)	0.209	(0.244)	-0.442	(0.229)
× Low SES	0.038	(0.158)	0.326	(0.221)	-0.244	(0.299)
× Female	-0.423	(0.149)	-0.276	(0.190)	-0.229	(0.251)
Same catchment	-0.088	(0.067)	-0.337	(0.127)	-0.030	(0.153)
× Medium-High SES	0.054	(0.065)	0.054	(0.135)	0.169	(0.177)
× Medium-Low SES	0.038	(0.065)	-0.071	(0.115)	0.164	(0.119)
× Low SES	0.060	(0.068)	0.011	(0.127)	0.324	(0.176)
× With scholarship	-0.046	(0.065)	0.066	(0.130)	-0.331	(0.135)
× Female	-0.088	(0.053)	-0.136	(0.084)	-0.053	(0.126)
× Type 2	-0.069	(0.048)	0.012	(0.090)	-0.157	(0.111)
Main City	0.380	(0.215)	0.494	(0.511)	-0.159	(0.572)
× Medium-High SES	-0.305	(0.260)	0.517	(0.427)	-0.035	(0.533)
× Medium-Low SES	-0.123	(0.218)	-0.355	(0.405)	-0.938	(0.600)
× Low SES	-0.566	(0.265)	-0.511	(0.478)	-1.397	(0.598)
× With scholarship	-0.046	(0.271)	0.133	(0.475)	0.622	(0.602)
× Female	-0.109	(0.159)	0.161	(0.339)	0.187	(0.487)
× Type 2	0.208	(0.163)	-0.264	(0.417)	-0.382	(0.504)
Paris	0.614	(0.199)	0.730	(0.391)	-0.105	(0.414)
× Medium-High SES	-0.306	(0.217)	0.535	(0.357)	0.654	(0.470)
× Medium-Low SES	0.093	(0.188)	-0.204	(0.330)	-0.030	(0.498)
× Low SES	-0.450	(0.238)	-0.501	(0.441)	0.014	(0.465)
× With scholarship	-0.037	(0.213)	-0.096	(0.398)	0.863	(0.551)
× Female	-0.025	(0.134)	-0.074	(0.330)	0.352	(0.363)
× Type 2	0.082	(0.159)	0.161	(0.336)	-0.343	(0.427)
Rent	-0.099	(0.050)	-0.129	(0.114)	0.072	(0.122)
× Medium-High SES	0.095	(0.061)	-0.077	(0.103)	0.052	(0.108)
× Medium-Low SES	0.020	(0.051)	0.119	(0.089)	0.236	(0.131)
× Low SES	0.139	(0.064)	0.154	(0.118)	0.302	(0.132)
× With scholarship	0.025	(0.059)	-0.042	(0.110)	-0.165	(0.138)
× Female	0.028	(0.036)	-0.038	(0.087)	-0.072	(0.107)
× Type 2	-0.036	(0.039)	0.056	(0.099)	0.068	(0.112)

Standard errors in parentheses.

Table C-5: Utility from accepting (2 of 2)

	Round 1		Round 2		Round 3	
GPA (Benchmark = General Track - Humanities & Social Sciences)						
Prep-sch. x GPA	-0.914	(0.212)	-0.682	(0.250)	-0.652	(0.283)
× Gen.-Sc.	0.785	(0.241)	0.992	(0.290)	0.411	(0.328)
× Tech. Track	0.702	(0.253)	-0.174	(0.582)	0.281	(1.181)
× Voc. Track.	0.702	(0.253)	-0.174	(0.612)	0.281	(1.232)
Tech. prog. x GPA	1.035	(0.228)	0.125	(0.471)	1.096	(0.553)
× Gen.-Sc.	0.034	(0.244)	0.471	(0.567)	0.812	(0.780)
× Tech. Track	0.496	(0.343)	0.874	(0.584)	1.198	(1.033)
× Voc. Track.	1.328	(0.682)	0.855	(0.905)	0.268	(5.030)
Voc. prog. x GPA	0.793	(0.214)	0.485	(0.416)	1.028	(0.584)
× Gen.-Sc.	0.083	(0.255)	0.928	(0.537)	0.343	(0.717)
× Tech. Track	0.543	(0.306)	0.830	(0.514)	0.496	(0.667)
× Voc. Track.	0.516	(0.316)	0.573	(0.473)	-0.016	(0.709)
Other prog. x GPA	1.231	(0.241)	0.530	(0.329)	1.139	(0.498)
× Gen.-Sc.	0.358	(0.260)	0.772	(0.398)	-0.060	(0.584)
× Tech. Track	0.498	(0.267)	0.031	(0.426)	0.212	(0.608)
× Voc. Track.	0.136	(0.398)	1.372	(0.652)	0.552	(1.087)
Same catchment x GPA	-0.036	(0.056)	0.062	(0.084)	0.005	(0.127)
× Gen.-Sc.	-0.051	(0.063)	-0.133	(0.102)	-0.112	(0.153)
× Tech. Track	-0.025	(0.084)	-0.111	(0.134)	-0.294	(0.194)
× Voc. Track.	-0.226	(0.121)	-0.001	(0.204)	-0.264	(0.283)
Paris x GPA	0.032	(0.118)	0.193	(0.277)	-0.258	(0.319)
× Gen.-Sc.	-0.080	(0.159)	-0.508	(0.394)	-0.032	(0.481)
× Tech. Track	0.263	(0.219)	-0.031	(0.469)	0.276	(0.604)
× Voc. Track.	-0.710	(0.307)	-0.700	(0.770)	0.007	(0.973)
Main city x GPA	0.414	(0.161)	0.542	(0.366)	0.235	(0.492)
× Gen.-Sc.	-0.309	(0.230)	-0.663	(0.544)	0.120	(0.699)
× Tech. Track	-0.138	(0.239)	0.073	(0.599)	-0.068	(0.894)
× Voc. Track.	-0.927	(0.324)	-0.802	(0.787)	-0.032	(1.206)
Rent x GPA	-0.075	(0.037)	-0.114	(0.081)	-0.000	(0.103)
× Gen.-Sc.	0.061	(0.051)	0.173	(0.123)	-0.071	(0.159)
× Tech. Track	0.020	(0.058)	-0.004	(0.130)	-0.007	(0.185)
× Voc. Track.	0.200	(0.078)	0.162	(0.179)	-0.058	(0.271)

Standard errors in parentheses.

Table C-6: Utility from Waiting & Drop Out

Common component		
Wait	-0.128	(0.056)
Drop Out X Round 1	-1.788	(0.118)
Drop Out X Round 2	-1.847	(0.120)
Drop Out X Round 3	-0.709	(0.132)
Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High X Wait	0.103	(0.046)
Medium-Low X Wait	0.062	(0.033)
Low X Wait	0.044	(0.039)
Medium-High X Drop out	-0.081	(0.113)
Medium-Low X Drop out	-0.118	(0.086)
Low X Drop out	-0.153	(0.076)
Scholarship Status (benchmark = Without Scholarship)		
With Scholarship X Wait	-0.064	(0.036)
With Scholarship X Drop out	-0.460	(0.096)
Sex (benchmark = Male)		
Female X Wait	-0.006	(0.029)
Female X Drop out	0.364	(0.078)
High School Program (Benchmark = General Track - Humanities & Social Sciences)		
General Track - Sciences X Wait	0.090	(0.039)
General Track - Sciences X Drop out	-0.623	(0.108)
Technological Track X Wait	-0.207	(0.033)
Technological Track X Drop out	0.593	(0.122)
Vocational Track X Wait	-0.463	(0.056)
Vocational Track X Drop out	0.593	(0.122)
GPA (Benchmark = General Track - Humanities & Social Sciences)		
GPA X Wait	0.181	(0.030)
GPA X Drop out	-0.247	(0.109)
General Track - Sciences X GPA X Wait	0.091	(0.044)
General Track - Sciences X GPA X Drop out	-0.175	(0.120)
Technological Track X GPA X Wait	-0.010	(0.054)
Technological Track X GPA X Drop out	0.132	(0.141)
Vocational Track X GPA X Wait	-0.013	(0.055)
Vocational Track X GPA X Drop out	-0.209	(0.186)
Unobserved Heterogeneity (benchmark = Type 1)		
Type 2 X Wait	0.009	(0.028)
Type 2 X Drop out	0.085	(0.081)
Additional results		
Scale parameter	0.098	(0.012)
Share of type 2	0.532	

Standard errors in parentheses.

C.2 Graduation Probability

Table C-7: Probability to graduate: part 1

Common component		
Program type (Benchmark = drop out)		
Bachelor	-2.166	(0.071)
Elite	-1.969	(0.079)
Tech. prog.	-4.279	(0.155)
Voc. prog.	-3.620	(0.139)
Other prog.	-2.957	(0.083)
Program major (Benchmark = STEM)		
EconLaw	1.880	(0.058)
Human	0.873	(0.060)
Services	2.194	(0.134)
Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High X Bachelor	0.192	(0.047)
Medium-High X Elite	-0.348	(0.059)
Medium-High X Tech. prog.	0.021	(0.092)
Medium-High X Voc. prog.	0.120	(0.085)
Medium-High X Other	0.097	(0.061)
Medium-Low X Bachelor	-0.031	(0.041)
Medium-Low X Elite	-0.586	(0.051)
Medium-Low X Tech. prog.	-0.161	(0.081)
Medium-Low X Voc. prog.	-0.071	(0.075)
Medium-Low X Other	-0.199	(0.054)
Low X Bachelor	-0.096	(0.046)
Low X Elite	-0.912	(0.063)
Low X Tech. prog.	-0.273	(0.091)
Low X Voc. prog.	-0.053	(0.080)
Low X Other	-0.349	(0.064)
Medium-High X EconLaw	-0.384	(0.050)
Medium-High X Human	-0.123	(0.054)
Medium-High X Services	-0.140	(0.090)
Medium-Low X EconLaw	-0.203	(0.043)
Medium-Low X Human	-0.033	(0.047)
Medium-Low X Services	-0.005	(0.079)
Low X EconLaw	-0.260	(0.051)
Low X Human	-0.086	(0.055)
Low X Services	0.041	(0.085)

Standard errors in parentheses.

Table C-8: Probability to graduate: part 2

Heterogeneity (continued)		
High School Program (Benchmark = General Track - Humanities & Social Sciences)		
General Track - Sciences X Bachelor	1.202	(0.050)
General Track - Sciences X Prep-sch.	1.568	(0.059)
General Track - Sciences X Tech. prog.	1.244	(0.117)
General Track - Sciences X Voc. prog.	0.507	(0.118)
General Track - Sciences X Other	1.670	(0.062)
Technological Track X Bachelor	-0.422	(0.055)
Technological Track X Prep-sch.	-1.202	(0.076)
Technological Track X Tech. prog.	-0.672	(0.125)
Technological Track X Voc. prog.	-0.033	(0.113)
Technological Track - Sciences X Other	0.617	(0.068)
Vocational Track X Bachelor	-1.869	(0.080)
Vocational Track X Prep-sch.	-1.202	(0.076)
Vocational Track X Tech. prog.	-2.198	(0.275)
Vocational Track X Voc. prog.	-0.449	(0.123)
Vocational Track - Sciences X Other	-1.219	(0.114)
General Track - Sciences X EconLaw	-1.625	(0.051)
General Track - Sciences X Human	-1.660	(0.053)
General Track - Sciences X Services	-1.346	(0.121)
Technological Track X EconLaw	-1.024	(0.056)
Technological Track X Human	-1.171	(0.062)
Technological Track X Services	-0.289	(0.115)
Vocational Track X EconLaw	-1.024	(0.056)
Vocational Track X Human	-1.326	(0.113)
Vocational Track X Services	-0.642	(0.130)
GPA (Benchmark = General Track - Humanities & Social Sciences)		
GPA X Bachelor	0.620	(0.046)
GPA X Prep-sch.	0.753	(0.052)
GPA X Tech. prog.	0.932	(0.110)
GPA X Voc. prog.	0.792	(0.101)
GPA X Other	0.087	(0.055)
General Track - Sciences X GPA X Bachelor	-0.047	(0.052)
General Track - Sciences X GPA X Prep-sch.	0.035	(0.059)
General Track - Sciences X GPA X Tech. prog.	-0.335	(0.123)
General Track - Sciences X GPA X Voc. prog.	-0.620	(0.123)
General Track - Sciences X GPA X Other	0.402	(0.063)
Technological Track X GPA X Bachelor	-0.115	(0.060)
Technological Track X GPA X Prep-sch.	0.090	(0.076)
Technological Track X GPA X Tech. prog.	-0.275	(0.132)
Technological Track X GPA X Voc. prog.	-0.695	(0.115)
Technological Track X GPA X Other	0.432	(0.073)
Vocational Track X GPA X Bachelor	0.230	(0.078)
Vocational Track X GPA X Prep-sch.	0.090	(0.076)
Vocational Track X GPA X Tech. prog.	0.209	(0.234)
Vocational Track X GPA X Voc. prog.	-0.440	(0.119)
Vocational Track X GPA X Other	0.573	(0.120)
GPA X EconLaw	1.880	(0.058)
GPA X Human	0.064	(0.044)
GPA X Services	2.194	(0.134)
General Track - Sciences GPA X EconLaw	-0.555	(0.051)
General Track - Sciences GPA X Human	-0.521	(0.053)
General Track - Sciences GPA X Services	0.148	(0.129)
Technological Track X EconLaw	-0.412	(0.060)
Technological Track X Human	-0.054	(0.068)
Technological Track X Services	0.442	(0.120)
Vocational Track X GPA X EconLaw	-0.412	(0.060)
Vocational Track X GPA X Human	-0.198	(0.111)
Vocational Track X GPA X Services	0.499	(0.129)

Standard errors in parentheses.

Table C-9: Probability to graduate: part 3

Heterogeneity (continued)		
Scholarship Status (Benchmark = Without Scholarship)		
With Scholarship X Bachelor	-0.261	(0.045)
With Scholarship X Elite	-0.478	(0.065)
With Scholarship X Tech. prog.	-0.282	(0.090)
With Scholarship X Voc. prog.	-0.181	(0.074)
With Scholarship X Other	-0.445	(0.065)
With Scholarship X EconLaw	0.158	(0.051)
With Scholarship X Human	0.267	(0.054)
With Scholarship X Services	0.146	(0.079)
Sex (Benchmark = Male)		
Female X Bachelor	-0.122	(0.032)
Female X Elite	-0.572	(0.041)
Female X Tech. prog.	-0.732	(0.072)
Female X Voc. prog.	-0.407	(0.066)
Female X Other	0.210	(0.044)
Female X EconLaw	0.250	(0.035)
Female X Human	0.481	(0.039)
Female X Services	0.565	(0.068)
Unobserved Type (Benchmark = Type 1)		
Type 2 X Bachelor	0.697	(0.034)
Type 2 X Elite	0.327	(0.043)
Type 2 X Tech. prog.	1.462	(0.089)
Type 2 X Voc. prog.	1.673	(0.085)
Type 2 X Other	0.958	(0.045)
Type 2 X EconLaw	-1.494	(0.040)
Type 2 X Human	-0.490	(0.040)
Type 2 X Services	-2.533	(0.094)

Standard errors in parentheses.

Table C-10: Probability to graduate: part 4

Switches		
Same as enrollment	0.824	(0.038)
Same as enrollment x rank 2	-0.097	(0.041)
Same as enrollment x rank 3	-0.192	(0.052)
Same as enrollment x rank 4	-0.255	(0.068)
Same as enrollment x rank 5 or more	-0.217	(0.047)
Bachelor to bachelor	-0.673	(0.063)
Bachelor to elite	-2.138	(0.059)
Bachelor to tech	-1.239	(0.115)
Bachelor to voc	-2.533	(0.106)
Bachelor to other	-2.083	(0.054)
Prep-sch to bachelor	-0.684	(0.071)
Prep-sch to elite	-0.583	(0.088)
Prep-sch to tech or voc	-1.617	(0.146)
Prep-sch to other	-1.289	(0.084)
Tech to bachelor	0.874	(0.068)
Tech to elite	0.015	(0.079)
Tech to tech	0.551	(0.129)
Tech to voc	-3.008	(0.162)
Tech to other	-2.494	(0.126)
Voc to bachelor	0.279	(0.063)
Voc to elite	-1.251	(0.088)
Voc to tech	-3.022	(0.202)
Voc to voc	-0.403	(0.103)
Voc to other	-2.631	(0.106)
Other to bachelor	-1.042	(0.079)
Other to elite	0.231	(0.074)
Other to tech	-0.820	(0.155)
Other to voc	-0.112	(0.101)
Other to other	-0.894	(0.087)
STEM to STEM	1.326	(0.042)
EconLaw to EconLaw	1.088	(0.046)
Human to Human	1.321	(0.044)
Services to services	1.708	(0.085)
Production to production	2.175	(0.088)
Production to sciences	1.473	(0.049)
Services to EconLaw	0.700	(0.042)

Standard errors in parentheses.

Table C-11: Probability to graduate: part 5

Program type (Benchmark = drop out)		
Bachelor - rank 2	-0.036	(0.116)
Bachelor - rank 3	-0.329	(0.150)
Bachelor - rank 4	-0.384	(0.189)
Bachelor - rank 5 or more	-0.285	(0.138)
Elite - rank 2	0.103	(0.122)
Elite - rank 3	-0.017	(0.157)
Elite - rank 4	0.031	(0.197)
Elite - rank 5 or more	0.351	(0.142)
Tech. prog. - rank 2	0.361	(0.146)
Tech. prog. - rank 3	0.433	(0.185)
Tech. prog. - rank 4	0.058	(0.243)
Tech. prog. - rank 5 or more	0.322	(0.174)
Voc. prog. - rank 2	0.277	(0.144)
Voc. prog. - rank 3	0.343	(0.184)
Voc. prog. - rank 4	-0.091	(0.243)
Voc. prog. - rank 5 or more	0.308	(0.176)
Other prog. - rank 2	0.030	(0.129)
Other prog. - rank 3	-0.123	(0.165)
Other prog. - rank 4	-0.196	(0.208)
Other prog. - rank 5 or more	-0.039	(0.150)
Program major (Benchmark = STEM)		
EconLaw - rank 2	0.192	(0.061)
EconLaw - rank 3	0.329	(0.082)
EconLaw - rank 4	0.284	(0.103)
EconLaw - rank 5 or more	0.411	(0.072)
Human - rank 2	0.007	(0.065)
Human - rank 3	0.204	(0.087)
Human - rank 4	0.006	(0.111)
Human - rank 5 or more	-0.005	(0.080)
Services - rank 2	-0.058	(0.093)
Services - rank 3	-0.027	(0.122)
Services - rank 4	0.140	(0.168)
Services - rank 5 or more	0.161	(0.123)

Standard errors in parentheses.

Table C-12: Probability to graduate: part 6

Heterogeneity x drop out dummmy		
SES Group (Benchmark = High SES)		
Medium-High X rank 2	0.027	(0.105)
Medium-High X rank 3	-0.051	(0.138)
Medium-High X rank 4	-0.049	(0.175)
Medium-High X rank 5 or more	-0.215	(0.127)
Medium-Low X rank 2	-0.018	(0.090)
Medium-Low X rank 3	0.058	(0.120)
Medium-Low X rank 4	-0.002	(0.149)
Medium-Low X rank 5 or more	-0.145	(0.104)
Low X rank 2	0.160	(0.096)
Low X rank 3	-0.116	(0.132)
Low X rank 4	-0.039	(0.162)
Low X rank 5 or more	-0.116	(0.118)
Scholarship - rank 2	0.169	(0.085)
Scholarship - rank 3	0.088	(0.115)
Scholarship - rank 4	0.016	(0.145)
Scholarship - rank 5 or more	0.183	(0.106)
Female - rank 2	-0.216	(0.068)
Female - rank 3	-0.073	(0.091)
Female - rank 4	-0.252	(0.114)
Female - rank 5 or more	-0.183	(0.081)
Type 2 - rank 2	0.064	(0.073)
Type 2 - rank 3	-0.056	(0.097)
Type 2 - rank 4	-0.102	(0.124)
Type 2 - rank 5 or more	-0.105	(0.091)

Standard errors in parentheses.

Table C-13: Probability to graduate: part 7

Heterogeneity x drop out dummmy		
GPA - rank 2	0.026	(0.076)
GPA - rank 3	0.230	(0.101)
GPA - rank 4	0.064	(0.127)
GPA - rank 5 or more	0.117	(0.101)
General Track - Sciences X GPA - rank 2	0.154	(0.099)
General Track - Sciences X GPA - rank 3	-0.191	(0.133)
General Track - Sciences X GPA - rank 4	0.086	(0.169)
General Track - Sciences X GPA - rank 5	0.293	(0.121)
Technological Track - Sciences X GPA - rank 2	-0.256	(0.114)
Technological Track - Sciences X GPA - rank 3	-0.212	(0.157)
Technological Track - Sciences X GPA - rank 4	-0.303	(0.199)
Technological Track - Sciences X GPA - rank 5	-0.399	(0.155)
Vocational Track - Sciences X GPA - rank 2	0.173	(0.140)
Vocational Track - Sciences X GPA - rank 3	-0.124	(0.200)
Vocational Track - Sciences X GPA - rank 4	-0.089	(0.251)
Vocational Track - Sciences X GPA - rank 5	0.116	(0.205)

Standard errors in parentheses.

C.3 State Transitions: Offer Probabilities

Table C-14: Probability to obtain new offer

Program type (Benchmark = Bachelor)		
Prep-sch.	-0.447	(0.095)
Tech. prog.	0.126	(0.097)
Voc. prog.	0.270	(0.097)
Other prog.	-0.128	(0.119)
Program major (Benchmark = STEM)		
EconLaw	-0.018	(0.081)
Human	0.186	(0.072)
Services	-0.126	(0.083)
Distance	0.008	(0.020)
Same catchment area	0.067	(0.079)
Paris	0.056	(0.145)
Main City	0.141	(0.238)
Main City X same catchment	-0.193	(0.218)
Rent	-0.022	(0.051)
Rent X same catchment	0.013	(0.042)
Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High	0.037	(0.060)
Medium-Low X Prep-sch.	0.090	(0.051)
Low X Prep-sch.	0.082	(0.059)
Other individual characteristics		
With Scholarship	0.008	(0.056)
Female	0.037	(0.041)
Type 2	-0.082	(0.053)
High School Program (Benchmark = General Track - Humanities & Social Sciences)		
General Track - Sciences	-0.021	(0.061)
Technological Track	-0.027	(0.064)
Vocational Track	-0.236	(0.101)
GPA (Benchmark = General Track - Humanities & Social Sciences)		
GPA	0.073	(0.041)
General Track - Sciences X GPA	-0.151	(0.053)
Technological Track X GPA	0.050	(0.070)
Vocational Track X GPA	0.284	(0.099)
Programs ranked higher in ROL		
Number of bachelor prog.	0.213	(0.015)
Number of prep-sch. prog.	0.031	(0.014)
Number of tech. prog.	0.031	(0.014)
Number of voc. prog.	0.031	(0.014)
Number of other prog.	-0.003	(0.016)
Other characteristics of current program and round		
Selectivity index	-0.013	(0.004)
Round 2 effect	0.041	(0.039)
Rank of the offer: 3	-0.050	(0.061)
Rank of the offer: 4	0.069	(0.066)
Rank of the offer: 5 or more	-0.017	(0.074)
Constant	-0.739	(0.352)

Standard errors in parentheses.

Table C-15: Probability to obtain a specific offer

Common component		
Program type (Benchmark = Bachelor)		
Prep-sch.	-0.835	(0.162)
Tech. prog.	-0.436	(0.199)
Voc. prog.	0.048	(0.207)
Other prog.	-0.745	(0.196)
Program major (Benchmark = STEM)		
EconLaw	0.231	(0.188)
Human	0.385	(0.169)
Services	-0.314	(0.159)
Distance	-0.127	(0.033)
Same catchment area	0.346	(0.105)
Paris	-0.673	(0.208)
Main City	-0.532	(0.359)
Main City X same catchment	0.887	(0.373)
Rent	0.067	(0.077)
Rent X same catchment	-0.192	(0.078)
Rank of the offer: 2	-0.384	(0.057)
Rank of the offer: 3	-0.403	(0.071)
Rank of the offer: 4	-0.394	(0.086)
Rank of the offer: 5 or more	-0.291	(0.077)
Interactions with selectivity index		
Round 1	-0.080	(0.022)
Round 2	-0.077	(0.024)
Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High	-0.046	(0.025)
Medium-Low X Prep-sch.	-0.055	(0.021)
Low X Prep-sch.	-0.045	(0.024)
Other individual characteristics		
With Scholarship	-0.022	(0.025)
Female	-0.009	(0.016)
Type 2	-0.018	(0.017)
High School Program (Benchmark = General Track - Humanities & Social Sciences)		
General Track - Sciences	-0.009	(0.019)
Technological Track	0.030	(0.024)
Vocational Track	0.019	(0.045)
GPA (Benchmark = General Track - Humanities & Social Sciences)		
GPA	0.035	(0.016)
General Track - Sciences X GPA	-0.069	(0.022)
Technological Track X GPA	0.040	(0.031)
Vocational Track X GPA	0.018	(0.054)

Standard errors in parentheses.

D Additional Counterfactual Tables

Table D-1: Sequential Program Characteristics - Matched Students

	(1)	(2)
Total improving match	2,358	0.136
Program Type and Major		
Changed Type Only	301	0.128
Changed Major Only	140	0.059
Changed Both	654	0.277
Other Program Characteristics		
Change in Distance		11.039
Probability Same Province		-0.064
Probability Same Catchment Area		-0.097
Probability Main City		0.029

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.

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"		
General	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	0.14	2.23
Type 2	0.13	2.21

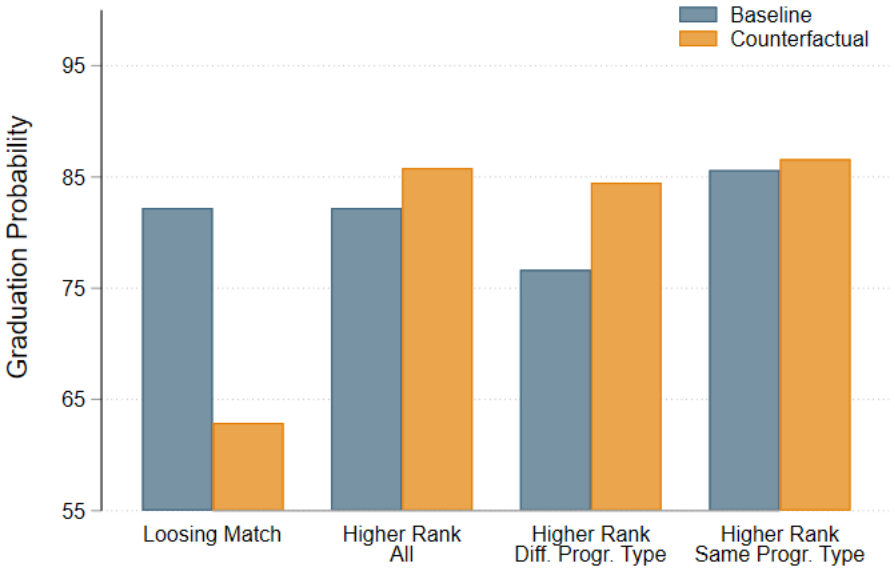
Notes. Column (1) shows the share of students without any round one offer, separately for students with different characteristics. Column (2) shows the average round one offer received, conditional on received one.

Table D-3: Offers by Groups

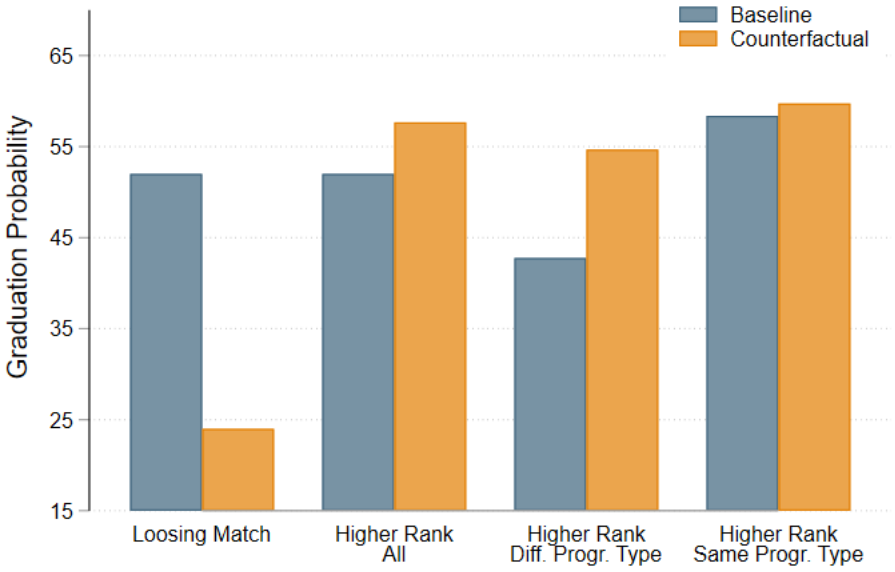
	Probability New Offer	
"SES Status"		
High	0.15	(.065)
Medium-High	0.15	(.056)
Medium-Low	0.21	(.07)
Low	0.17	(.056)
"High-School Track"		
General	0.17	(.073)
Tehnological	0.16	(.051)
Vocational	0.18	(.065)
"Scholarship Status"		
Eligible	0.18	(.062)
Not-Eligible	0.17	(.069)
"Unobserved Type"		
Type 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.

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



(a) General high-school track



(b) Technical and vocational high-school track