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

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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 across socio-economic groups. We use 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 substantial welfare gains for all groups from using a multi-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 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 262 kilometers closer to home. Zooming in on the 38% of students who do not receive their first-ranked alternative in Round 1, this increases to a sizeable distance of 579 kilometers. However, the gains are not equally distributed. The two highest SES groups gain the equivalent of 596 and 605 kilometers, while the two lowest experience a somewhat smaller gain, equivalent to 541 and 566 kilometers. Third, the sequential mechanism strongly affects the number of successful matches, and, to a lesser extent, the type of program and major choices. In the affected group, the total number of unmatched students decreases from 29% to 18%. The number of students in the (most common) college type of "bachelor" programs remains constant, but high SES students increasingly match with elite prep-school programs, and low SES with technical and vocational programs. In terms of majors, we see particularly more STEM and Services.

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]

[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

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 (Bó & Hakimov, 2016; Luflade, 2018; Chen & Pereyra, 2019; Grenet et al., 2019). Focusing on the timing of offer acceptance, our paper is closest to Grenet et al. (2019), 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.
We explore an alternative explanation 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

-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.

[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.

mechanisms (Agarwal et al., 2021; Waldinger, 2021; Larroucau & Ríos, 2021). 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 students' higher education choices, in particular joint choice of institution and field of study (see Altonji et al., 2016; and Patnaik et al., 2020 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 The French Higher Education System and the College Admission Procedure

Primary, secondary, and higher education in France are centralized and regulated by the Ministry of Education. France is partitioned into 30 catchment areas, called *Académies*,[4]

[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]A map of the French catchment areas is presented in Figure A.1.

each of which is responsible for organizing and administering educational policies within its area, following the directives of 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*), which will determine their post-secondary education choice set upon high school graduation. 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.

A semi-centralized system. For the purpose of understanding applications and admissions to post-secondary programs, the French system can be described as semi-centralized. On the one hand, a majority of programs participate in a nationwide centralized assignment procedure operated by the Ministry of Higher Education. This procedure involves students submitting rank-ordered lists (ROLs) to a clearinghouse via an online platform, programs assigning priorities to their applicants, and the clearinghouse using a pre-specified algorithm to assign students to programs. On the other hand, other programs operate "off-platform", that is, collect applications and decide on admissions in a decentralized manner. Our analysis and model in Section 4 focuses on students' choices as they participate in the centralized procedure, and we simply take as given the existence of off-platform options. However, off-platform options matter for the outcome of the centralized procedure: receiving an offer from an off-platform program can induce students to decline the assignment received from the centralized procedure, thereby creating a vacancy that, in the case of a multi-round mechanism like the French APB, can be offered to another on-platform applicant. There is no unique or definitive criterion that determines whether or not a program participates in the centralized admission procedure, but off-platform programs generally pertain to one of

three groups (Cour des Comptes, 2017): programs accredited by an agency other than the Ministry of Higher Education; programs jointly offered by multiple institutions (i.e. "double diplomas"); and programs wishing to retain full control over their admission calendar and decisions. Table 1 provides an overview of the different types of higher-education programs in France. The top and middle panels of Table 1 gather programs participating in the centralized admission procedure, which we discuss in detail below. The bottom panel summarizes characteristics of off-platform programs. An important take-away from the table is that the distinction between on- and off-platform programs does not perfectly reflect differences in other characteristics that typically determine preferences for programs —public (typically free) and private programs can be found both in- and off-platform, and so are different fields of study, such as STEM, Econ./Law/Business, or Humanities. As consequence, many high-school graduates wishing to enter higher education in the given year both participate in the centralized procedure and submit applications off platform.

We now proceed to present two unique features of the centralized assignment procedure that are important for the rest of this paper.

A centralized procedure with multiple rounds. The first one, motivating the research question, is that it is a multi-round assignment mechanism. After receiving an assignment from the platform, students can choose between three options. The student can *accept* the assignment immediately and proceed with enrollment; the student can refuse the assignment and *drop out* of the platform, thereby returning her assignment to the vacancy pool; and the student can 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.[5][6] 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*

[5]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.

[6]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.

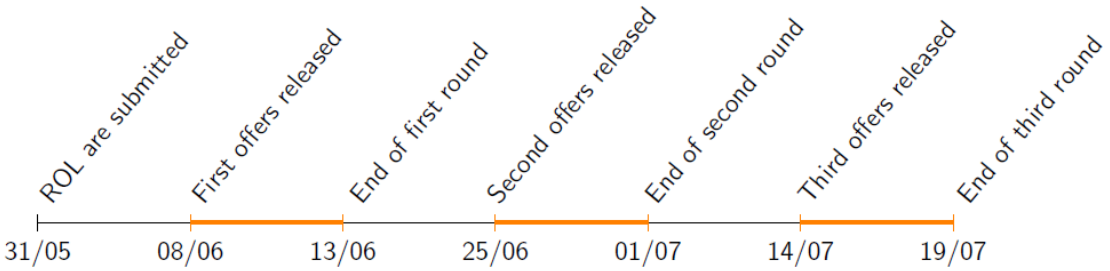
Table 1: Types of post-secondary programs in France

ON-PLATFORM PROGRAMS EXCLUDING HIGH-SCHOOL PERFORMANCE FROM THEIR ADMISSION CRITERIA	
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)
ON-PLATFORM PROGRAMS INCLUDING HIGH-SCHOOL PERFORMANCE IN THEIR ADMISSION CRITERIA	
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]	
Bachelors and other programs offered by public universities	(1) Programs accredited by other agencies than the Ministry of higher education —e.g., all programs in nursing and paramedical fields (accr. by the Ministry of Health and Social Affairs); most arts programs (accr. by the Ministry of Culture) (2) Programs jointly offered by multiple institutions (i.e. delivering "double diplomas") (3) competitive programs (e.g. programs in the selective Paris Dauphine and several political science institutes)
Programs offered by private schools	24 of the 36 private business schools recruiting after high-school 9 of the 76 private engineering schools recruiting after high-school

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)

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.

Figure 1: Multiple assignment rounds timeline in 2015



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.

ROLs, priorities, and the assignment algorithm. The other unique feature of the French APB procedure consists in the rules of the assignment mechanism itself. Regarding ROLs, rules are pretty straightforward: students can rank up to 36 programs, with a maximum of twelve per *type* of program. The four *types* of programs —Bachelor programs, technical programs, prep-school programs, and vocational programs— are described in Table 1. When it comes to priorities, rules are much more complex and obscure. From the perspective of students, no priority score is known at the time of application, nor at any point during or after the process. On the one hand, prep-school programs, technical programs, and vocational programs, typically do not disclose the criteria they use to determine priority, and are simply known to consider academic performance as a criterion. Bachelor programs, on the other hand, are not permitted by law to use academic performance as a determinant of applicants' priority. They rely on coarse priority groups defined based on the applicant's residential location[7]) and the absolute rank of the program in the applicant's ROL. 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 ROL in the determination of their priority to programs was unknown to students, who were simply aware of the within-region advantage. Given the students' ROLs and the priorities set by each program, matches are determined

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

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.[8] As a matter of fact, the only guideline provided to students was to report their preferences truthfully in their ROLs.

3 Data and Descriptive Evidence

The empirical analysis of this paper uses administrative data from French Ministry of Higher Education (Research and Innovation department, SIES). For every student participating in the college assignment procedure, the data provide demographics, residential ZIP code, a high-school identifier, the track and major chosen in high school, high school grades (which we use to construct a Grade Point Average, GPA), as well as the ROL submitted to the APB platform. The data also show the assignment offer received by the student in each round (if any), as well as her decision (accept, drop out, or delay) for that round. We supplement these data with publicly available information about the cost of housing in France's major cities. Details about the data sources and the definition of key variables are provided in Appendix A.

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.[9] Descriptive statistics are shown in Table A-1. Students submit on average slightly less than seven choices in their ROL. Of importance given our research question, students' final assignment is on average ranked higher in their ROL than the first offer they receive. We return to this feature below when we explore the benefits to choosing the option to *delay*.

In the rest of this section, we document the use by students of their option to delay in the

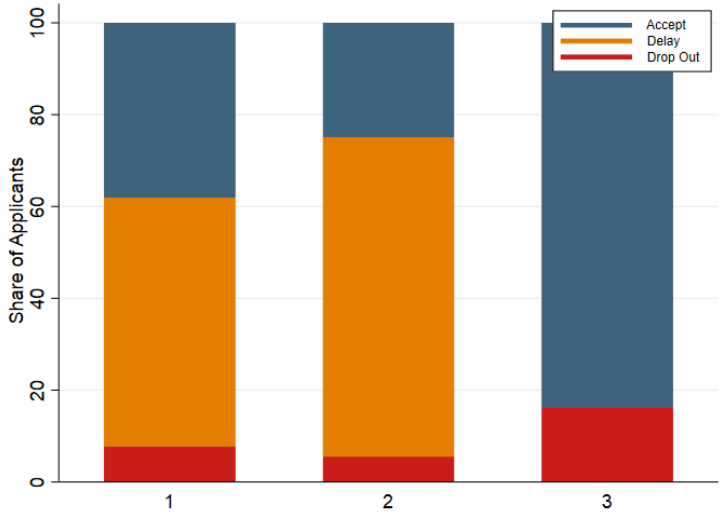
[8] Note also that "past admissions cutoffs" available to applicants in many other context are not disclosed in this setting.

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

different rounds of the assignment procedure. We show that there are gains from delaying, in the sense that a substantial fraction of the students who *delay* eventually receive a higher-ranked offer in a subsequent round. We also show 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.

Fact 1: Many but not all students choose to *delay* acceptance. First, 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 delay, 85% of participants accept their assignment while the rest drops out.

Figure 2: Decision shares by round



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.

Fact 2: There are significant benefits to choosing the *delay* option. Table 2 illustrates the expected benefits of choosing the delay option. Eighteen percent of the students

choosing to delay in Round 1 receive a new (higher-ranked) offer in Round 2. 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, and this offer is ranked on average 2.53 ranks above the offer they hold on to at the end of Round 2.

Table 2: Share of students receiving new offers after choosing *delay*

	Share
Receiving better offer in Round 2, cond. on choosing *delay* in Round 1	0.18
Receiving better offer in Round 3, cond. on choosing *delay* in Rounds 1 and 2	0.19
Mean rank improvement in Round 2 if better offer	2.48
Mean rank improvement in Round 3 if better offer	2.53

This table reports the share of students receiving a new (higher-ranked) offer conditional on choosing delay in the previous rounds, as well as the average difference in ranks between their new offer and the one they were holding on to.

In Table 3, 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) 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 3: Enrollment and graduation outcomes of students choosing *delay* in the first round as a function of later-round offers

	Enrolling		Not earning a degree			
	(1)	(2)	(3)	(4)	(5)	(6)
Receive better offer	0.034	0.037	-0.028	-0.030	-0.016	-0.023
	(0.003)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Rank Initial Offer	No	Yes	No	Yes	No	Yes
High-School Track	No	Yes	No	Yes	No	Yes
High-School GPA	No	Yes	No	Yes	No	Yes
Obs.	78,884	78,884	78,884	78,884	63,582	63,582
Baseline	80.60	80.60	30.01	30.01	20.55	20.55

The table shows estimates for β_1 from estimating Eq. (1) on the sample of those students who receive first round offer *and* choose to delay in the first round (Columns (1) to (4)); or those who, in addition, do enroll in some higher-education program in 2015 (Columns (5) 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. Table 4 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 1 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 5 reports the share of students

Table 4: Enrollment and graduation outcomes of students without a first-round offer as a function of later-round offers

	Enrolling		Not earning a degree			
	(1)	(2)	(3)	(4)	(5)	(6)
Receive 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)
High-School Track	No	Yes	No	Yes	No	Yes
High-School GPA	No	Yes	No	Yes	No	Yes
Obs.	58,526	58,526	58,526	58,526	20,224	20,224
Baseline	34.56	34.56	73.45	73.45	46.77	46.77

The table shows estimates for β_1 from estimating Eq. (1) on the sample of those students who do not receive an offer in the first round (Columns (1) to (4)); or those who, in addition, do enroll in some higher-education program at some point (Columns (5) and (6)).

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

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

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 6 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 7, we restrict our attention to students holding an offer from their second-ranked program,

Table 6: Holding an offer from a lower-ranked program is associated with a larger probability to delay acceptance.

	Round 1		Round 2	
	(1)		(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.

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 7: 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 is most 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, potentially augmented by an early acceptance advantage ($e_{j_t,t}(S_i, \tau)$):

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

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: $\omega_i = \omega(S_i, \tau)$. 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:

$$\Omega_{it} = (S_i, \tau, \mathcal{R}_i, t, j_t). \tag{5}$$

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

$$v_{i3t} = u_{0t}(S_i, \tau) \tag{6}$$

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:

$$\Pr(d_{it}^{DDC} = k|\Omega_{it}) = \frac{\exp(v_{ikt})}{\exp(v_{i1t}) + \exp(v_{i2t}) + \exp(v_{i3t})} \tag{7}$$

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:

$$\bar{V}_{it+1}(\Omega_{it}, j_{t+1}) = \ln(\exp(v_{i1t+1}) + \exp(v_{i2t+1}) + \exp(v_{i3t+1})) \tag{8}$$

Substituting this in (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 option is always available, i.e. some of the $v_{ikt} = -\infty$. Student i does not have the possibility to delay if they receive an offer to their top-ranked program. A student without an offer in the current round cannot choose to accept. As mentioned before, in the final period a terminal action needs to be chosen.

4.3 Graduation outcome

5 Identification and estimation

We first discuss the identification and parameterization 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:

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

where is Ω_{it} is defined in (5). 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 we impose for estimation the following flexible parametric structure. While these parametric restrictions are not needed for identification, these yield substantial precision gains.

Program utility. We parameterize the utility function of a student i when being matched to a program $j \in \mathcal{J}$ as follows:

$$
\begin{aligned}
u_j(S_i,\tau) = \sum_k \mathbf{1}[\text{Prog_Type}_j = k] \cdot \Big(\alpha_0^{(k,\tau)} + \alpha_1^{(k)}\mathbf{1}[\text{female}_i] + \sum_{s=2}^{4}\alpha_2^{(k,s)}\mathbf{1}[\text{SES}_i = s] + \alpha_3^{(k)}\text{GPA}_i + \dots \\
\sum_{s=2}^{4}\mathbf{1}[\text{hs_track}_i = s](\alpha_4^{(k,s)} + \alpha_5^{(k,s)}\text{GPA}_i)\Big) \\
+ \sum_k \mathbf{1}[\text{Field_Study}_j = k]\Big(\beta_0^{(k,\tau)} + \beta_1^{(k)}\mathbf{1}[\text{female}_i] + \sum_{s=2}^{4}\beta_2^{(k,s)}\mathbf{1}[\text{SES}_i = s] + \beta_3^{(k)}\text{GPA}_i + \dots \\
\sum_{s=2}^{4}\mathbf{1}[\text{hs_track}_i = s](\beta_4^{(k,s)} + \beta_5^{(k,s)}\text{GPA}_i)\Big) \\
+ \gamma_1\text{distance}_{ij} + \gamma_2\text{same_catchment}_{ij} + \gamma_3\text{main_city}_j + \gamma_4\text{rent}_j
\end{aligned}
$$

where hs_track_i captures the three tracks, but also splits the general track in a sub-track that focuses on sciences, and a benchmark sub-track that focuses on humanities or social sciences, distance_{ij} is the kilometer distance between i's home and the location of program j, rent_j is the average rent if the program is located in a major city j, and $\text{same_catchment}_{ij}$ and main_city_j are indicator variables equal to 1 if i lives in the same catchment area as j is

located and j is located in a major city, respectively. This set of variables flexibly captures the location characteristics of programs. We allow for heterogeneity in preferences for program types, and majors according to 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).[10]

Early acceptance utility. The early acceptance utility is parametrized as follows:

$$
\begin{aligned}
e_{jt}(S_i,\tau) = \text{distance}_{i,j_t} \cdot \Big(b_0^{(\tau)} + b_1 \mathbf{1}[\text{female}_i] + \sum_{s=2}^{4} b_2^{(s)} \mathbf{1}[\text{SES}_i = s] + b_3^{(s)} \text{GPA}_i + \dots \\
\sum_{s=2}^{4} \mathbf{1}[\text{hs_track}_i = s](b_4^{(s)} + b_5^{(s)} \text{GPA}_i)\Big) \\
+ \text{rent}_{j_t} \cdot \Big(b_6^{(\tau)} + b_7 \mathbf{1}[\text{female}_i] + \sum_{s=2}^{4} b_8^{(s)} \mathbf{1}[\text{SES}_i = s] + b_9^{(s)} \text{GPA}_i + \dots \\
\sum_{s=2}^{4} \mathbf{1}[\text{hs_track}_i = s](b_{10}^{(s)} + b_{11}^{(s)} \text{GPA}_i)\Big) \\
+ \text{main_city}_{j_t} \cdot \Big(b_{12}^{(\tau)} + b_{13} \mathbf{1}[\text{female}_i] + \sum_{s=2}^{4} b_{14}^{(s)} \mathbf{1}[\text{SES}_i = s] + b_{15}^{(s)} \text{GPA}_i + \dots \\
\sum_{s=2}^{4} \mathbf{1}[\text{hs_track}_i = s](b_{16}^{(s)} + b_{17}^{(s)} \text{GPA}_i)\Big)
\end{aligned}
$$

To keep the model estimation tractable, we include only the program characteristics that capture mobility concerns. We include distance, rent and a dummy indicating whether the program is located in a major city.

[10] 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.

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 drop out from the platform Finally,

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

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 $\Pr(j_{t+1} = j'|\Omega_{it})$ by using their information (5). We consider a parametric, but flexible relationship 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.[11] This index enters with a round-specific effect and interactions with observed characteristics

[11] 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.

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 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 (7) 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, 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.[12] 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.

[12] 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.

5.3.1 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 (8) 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 $\sum_{j' \in \mathcal{R}_i^{j_t} \cup \{j_t\}} \Pr(j_{t+1} = j'|\Omega_{it}) = 1$.

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.[13]

[13] 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.

5.4 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.[14] 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.[15]

6 Estimation Results and Counterfactual Simulations

6.1 Program utility

The results on the utility of each program are summarized in Table 8, Table 9 and Table 10.[16] To interpret them correctly, it is important to note that we report the utility parameters

[14] 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.

[15] 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.

[16] 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

divided by a scale parameter σ. To compare them to other utility estimates (early acceptance, waiting costs and drop out), they should be multiplied by our estimate $\sigma = 0.138$. This estimate implies that the standard deviation of the "trembling hand" error in the ROL is quite small as it amounts to about 14% of a standard deviation in the taste shocks that enter the dynamic choice model. The utility parametrization involves several indicator variables; *Bachelor program* and *STEM* and *Production* serve as benchmark categories for programs type and field of study.[17] To interpret the role of individual characteristics, the benchmark is a male, high-SES, not eligible to a scholarship, who graduated high-school in the general track in a non-science major and with unobservable type 1.

The first part of Table 8 shows the utility of different program types and majors for the benchmark group, as well as the variables related to proximity and housing. From the latter, we can conclude that students value proximity. This is reflected in the negative coefficient on distance, as well as in the nonlinear effects coming from staying in the catchment area. The distance parameter also helps to make sense of the magnitude of other utility estimates. Note that distance is scaled in 100 km and can be used to quantify the utility impact of other variables. For example, prep-school programs are, on average, valued less than Bachelor programs by the benchmark group with a GPA of 10 out of 20, equivalent to an increase in distance of 82 km ($= 100 \times ((7.883 - 10 \times 0.700)/1.079) = 82$). To capture differences in local amenities and housing conditions, we allow for different preferences to study in the main cities of France. Furthermore, within these cities, we let the impact differ by local rents. This should not be interpreted as a causal effect of rents, but rather as a proxy for local amenities. Indeed, we find that at 0 rent, students prefer not to live in a city, but they prefer locations with better amenities.

The rest of Table 8, as well as Tables 9 and 10 describe the heterogeneity in program preferences, i.e. how utilities differ for the students outside of the benchmark group. The main findings are the following. As compared to the benchmark group, lower SES students are more likely to consider Bachelor programs over all other programs. Female students have a relatively lower preference for a STEM field than any for other field. The coefficients

the CCP are available upon request.

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

Table 8: Program utility (part 1 of 3)

Common component		
Program type (Benchmark = Bachelor)		
Prep-sch.	-7.883	(0.268)
Tech. prog.	-2.282	(0.389)
Voc. prog.	-2.962	(0.404)
Other prog.	-2.967	(0.328)
Program major (Benchmark = STEM)		
EconLaw	-3.438	(0.325)
Human	-2.827	(0.292)
Services	0.747	(0.377)
Distance	-1.079	(0.008)
Same catchment area	1.599	(0.016)
Main City	-0.431	(0.032)
Rent	0.199	(0.006)
Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High X Prep-sch.	-0.364	(0.068)
Medium-High X Tech. prog.	-0.033	(0.076)
Medium-High X Voc. prog.	0.286	(0.081)
Medium-High X Other	-0.072	(0.074)
Medium-Low X Prep-sch.	-0.642	(0.059)
Medium-Low X Tech. prog.	-0.217	(0.067)
Medium-Low X Voc. prog.	-0.057	(0.071)
Medium-Low X Other	-0.553	(0.067)
Low X Prep-sch.	-0.792	(0.071)
Low X Tech. prog.	-0.539	(0.075)
Low X Voc. prog.	-0.166	(0.077)
Low X Other	-0.747	(0.076)
Medium-High X EconLaw	-0.479	(0.077)
Medium-High X Human	0.156	(0.068)
Medium-High X Services	-0.275	(0.076)
Medium-Low X EconLaw	-0.263	(0.065)
Medium-Low X Human	-0.209	(0.060)
Medium-Low X Services	0.050	(0.066)
Low X EconLaw	-0.314	(0.075)
Low X Human	-0.392	(0.069)
Low X Services	0.370	(0.071)

Standard errors in parentheses.

Table 9: Program utility (part 2 of 3)

Heterogeneity (continued)		
High School Program (Benchmark = General Track - Humanities & Social Sciences)		
General Track - Sciences X Prep-sch.	1.717	(0.328)
General Track - Sciences X Tech. prog.	5.066	(0.441)
General Track - Sciences X Voc. prog.	3.193	(0.495)
General Track - Sciences X Other	1.545	(0.383)
Technological Track X Prep-sch.	1.322	(0.563)
Technological Track X Tech. prog.	1.673	(0.501)
Technological Track X Voc. prog.	3.417	(0.501)
Technological Track - Sciences X Other	1.473	(0.491)
Vocational Track X Prep-sch.	1.322	(0.563)
Vocational Track X Tech. prog.	0.229	(0.837)
Vocational Track X Voc. prog.	1.720	(0.683)
Vocational Track - Sciences X Other	1.544	(0.701)
General Track - Sciences X EconLaw	0.232	(0.374)
General Track - Sciences X Human	2.059	(0.347)
General Track - Sciences X Services	-2.762	(0.451)
Technological Track X EconLaw	1.480	(0.491)
Technological Track X Human	2.644	(0.437)
Technological Track X Services	-1.566	(0.454)
Vocational Track X EconLaw	1.480	(0.491)
Vocational Track X Human	1.796	(0.648)
Vocational Track X Services	-0.757	(0.553)
GPA (Benchmark = General Track - Humanities & Social Sciences)		
GPA X Prep-sch.	0.700	(0.021)
GPA X Tech. prog.	0.310	(0.035)
GPA X Voc. prog.	0.107	(0.037)
GPA X Other	0.299	(0.028)
General Track - Sciences X GPA X Prep-sch.	-0.107	(0.025)
General Track - Sciences X GPA X Tech. prog.	-0.432	(0.040)
General Track - Sciences X GPA X Voc. prog.	-0.282	(0.045)
General Track - Sciences X GPA X Other	-0.026	(0.033)
Technological Track X GPA X Prep-sch.	-0.192	(0.044)
Technological Track X GPA X Tech. prog.	-0.093	(0.045)
Technological Track X GPA X Voc. prog.	-0.121	(0.045)
Technological Track X GPA X Other	-0.087	(0.043)
Vocational Track X GPA X Prep-sch.	-0.192	(0.044)
Vocational Track X GPA X Tech. prog.	0.007	(0.070)
Vocational Track X GPA X Voc. prog.	0.212	(0.058)
Vocational Track X GPA X Other	-0.003	(0.058)
GPA X EconLaw	-3.438	(0.325)
GPA X Human	0.409	(0.026)
GPA X Services	0.747	(0.377)
General Track - Sciences GPA X EconLaw	-0.422	(0.033)
General Track - Sciences GPA X Human	-0.529	(0.031)
General Track - Sciences GPA X Services	-0.173	(0.041)
Technological Track X EconLaw	-0.357	(0.043)
Technological Track X Human	-0.493	(0.039)
Technological Track X Services	-0.018	(0.041)
Vocational Track X GPA X EconLaw	-0.357	(0.043)
Vocational Track X GPA X Human	-0.308	(0.054)
Vocational Track X GPA X Services	-0.124	(0.048)

Standard errors in parentheses.

Table 10: Program utility (part 3 of 3)

Heterogeneity (continued)		
Scholarship Status (Benchmark = Without Scholarship)		
With Scholarship X Prep-sch.	0.042	(0.075)
With Scholarship X Tech. prog.	-0.287	(0.076)
With Scholarship X Voc. prog.	-0.209	(0.075)
With Scholarship X Other	-0.284	(0.079)
With Scholarship X EconLaw	0.170	(0.076)
With Scholarship X Human	0.037	(0.068)
With Scholarship X Services	0.175	(0.068)
Sex (Benchmark = Male)		
Female X Prep-sch.	-0.640	(0.047)
Female X Tech. prog.	-1.557	(0.054)
Female X Voc. prog.	-1.330	(0.055)
Female X Other	-0.838	(0.052)
Female X EconLaw	0.437	(0.051)
Female X Human	0.989	(0.048)
Female X Services	1.955	(0.052)
Unobserved Type (Benchmark = Type 1)		
Type 2 X Prep-sch.	-2.012	(0.048)
Type 2 X Tech. prog.	-2.643	(0.064)
Type 2 X Voc. prog.	-2.660	(0.068)
Type 2 X Other	-3.819	(0.069)
Type 2 X EconLaw	3.353	(0.071)
Type 2 X Human	-0.886	(0.053)
Type 2 X Services	5.817	(0.070)

Standard errors in parentheses.

associated with high school tracks and GPA, which are flexibly interacted, point to substantial heterogeneity in preferences for types of programs and college emajors.

Table 10 concludes with the heterogeneity that is not explained by observable characteristics. 56% of the sample is estimated to be of unobserved type 2. This type is capturing a much lower willingness to consider alternatives to a Bachelor program. For example, the difference in utility derived from attending a prep-school program instead of a Bachelor is equivalent to attending a program 186 km closer to home, all other things constant. This type is also much less likely to consider a program in Humanities and more likely to consider EconLaw or Services. The magnitude of these estimates show the importance of allowing for unobserved heterogeneity in preferences for post-secondary programs.

6.2 Early acceptance

We now discuss the parameters entering the second stage of the model, starting with the parameters of the early acceptance advantage. Estimates are shown in Table 11.

Because of housing considerations, accepting a program early in the process can have substantial benefits for students. Table 11 reveals that students are indeed more likely to accept a program early if it is further away. For the benchmark student, accepting a program that is 100 km away in an early round, rather than the last one, increases their utility by 0.066 utils. To interpret this number, note that this is about equivalent to half the disutility to travel 100 km for a program, which is estimated to be -0.149 ($= -1.079 \times 0.138$). This suggests that early knowledge on where to enroll can partly offset the travel cost for a large group of students (abstracting from the nonlinear effects of living in the region where the program is located). However, caution is advised as the estimate is not precise. As student demographic and academic background might affect the set of available housing options, we allow for heterogeneity in early acceptance utility. However, we find that the differences along these dimensions are typically small and without a clear pattern. Another variable that captures housing considerations is the proxy for local amenities (the *Main City* indicator and the interaction with local rents). The effects differ substantially by GPA, especially for the benchmark student in the non-sciences general track. A GPA of 10 out of 20 yields small effects of city and rent. Higher GPAs make students accept earlier places in cities, and

Table 11: Utility from Early Acceptance

Distance		
Distance	0.066	(0.081)
Distance X Female	0.016	(0.018)
Distance X Type 2	-0.014	(0.018)
Distance X Medium-High SES	-0.056	(0.026)
Distance X Medium-Low SES	-0.052	(0.022)
Distance X Low SES	-0.096	(0.029)
Distance X With Scholarship	0.049	(0.028)
Distance X General Track - Sciences	0.068	(0.108)
Distance X Technological Track	0.002	(0.152)
Distance X Vocational Track	-0.035	(0.270)
Distance X GPA	0.005	(0.006)
Distance X GPA X General Track - Sciences	-0.007	(0.009)
Distance X GPA X Technological Track	0.001	(0.013)
Distance X GPA X Vocational Track	-0.005	(0.021)
Main City		
Main City	-2.275	(0.474)
Main City X Female	-0.053	(0.096)
Main City X Type 2	0.256	(0.094)
Main City X Medium-High SES	-0.160	(0.151)
Main City X Medium-Low SES	-0.075	(0.126)
Main City X Low SES	-0.114	(0.144)
Main City X With Scholarship	0.156	(0.142)
Main City X General Track - Sciences	1.227	(0.612)
Main City X Technological Track	1.854	(0.859)
Main City X Vocational Track	0.439	(1.245)
Main City X GPA	0.196	(0.040)
Main City X GPA X General Track - Sciences	-0.113	(0.052)
Main City X GPA X Technological Track	-0.189	(0.076)
Main City X GPA X Vocational Track	-0.075	(0.100)
Rent		
Rent	0.332	(0.090)
Rent X Female	0.016	(0.019)
Rent X Type 2	-0.038	(0.019)
Rent X Medium-High SES	0.032	(0.031)
Rent X Medium-Low SES	0.015	(0.025)
Rent X Low SES	0.033	(0.030)
Rent X With Scholarship	-0.009	(0.029)
Rent X General Track - Sciences	-0.218	(0.115)
Rent X Technological Track	-0.331	(0.175)
Rent X Vocational Track	-0.145	(0.259)
Rent X GPA	-0.031	(0.008)
Rent X GPA X General Track - Sciences	0.020	(0.010)
Rent X GPA X Technological Track	0.032	(0.016)
Rent X GPA X Vocational Track	0.017	(0.021)

Standard errors in parentheses.

locations where rents (i.e. amenities) are lower.

6.3 Waiting costs and drop out utility

Estimates for the waiting costs and drop out utility are shown in Table 12. Note that the tables report the negative of the waiting costs parameters so they should be interpreted as utility, rather than disutility.

The benchmark student experiences a cost from using the drop out option, which increases further when students do not belong to the highest SES group or when they are on a scholarship. On the contrary, type-2 and female students have better outside options.

To interpret the waiting costs, Figure 3 plots them for the students who have this option in round 1, split by SES groups (combining the two lowest and two highest categories). Note that we plot them in distance-equivalent terms by dividing them by the scale parameter (0.138), multiplied with the estimate in 8 on the disutility of a kilometer (1.079/100). This figure shows that waiting costs are high (median=257 kilometers), meaning that many students would accept an offer 200 to 300 kilometers further from home, just to avoid having to wait another round. The figure also reveals that waiting costs are substantially higher for low SES students, who might not benefit as much from a sequential mechanism.

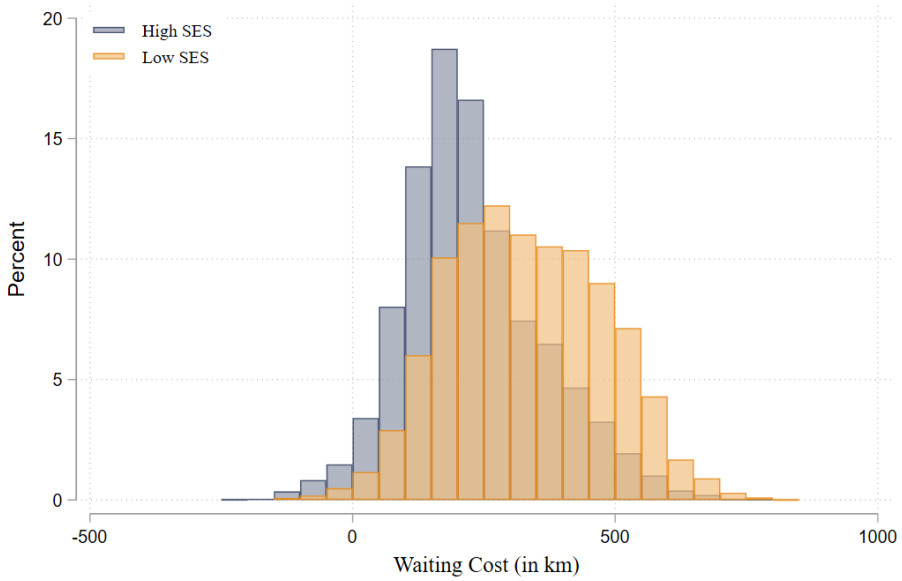
To better interpret the magnitude of waiting costs, relative to other aspects of college decisions, we also express the utility gains from enrolling in programs of different types (relative to a benchmark Bachelor program) and in different fields of study (relative to the STEM or Production benchmark) in distance-equivalent terms. Figure 4 shows the predicted distribution of waiting costs in comparison to the relative valuation of programs types (top panel) and fields of study (bottom panel). We find that, overall, the magnitude of waiting costs could easily offset the utility gains from being assigned to a program in more preferred type or field of study. In other words, for many students, differences in utility between majors or program types are not large enough to overcome the cost of delaying acceptance.

Table 12: Utility from Waiting & Drop Out

Common component		
Wait	-1.179	(0.189)
Drop Out X Round 1	-1.342	(0.175)
Drop Out X Round 2	-0.983	(0.174)
Drop Out X Round 3	-0.408	(0.174)
Heterogeneity		
SES Group (Benchmark = High SES)		
Medium-High X Wait	-0.053	(0.053)
Medium-Low X Wait	-0.007	(0.045)
Low X Wait	-0.052	(0.050)
Medium-High X Drop out	-0.395	(0.049)
Medium-Low X Drop out	-0.260	(0.041)
Low X Drop out	-0.362	(0.046)
Scholarship Status (benchmark = Without Scholarship)		
With Scholarship X Wait	-0.123	(0.049)
With Scholarship X Drop out	-0.258	(0.046)
Sex (benchmark = Male)		
Female X Wait	-0.059	(0.035)
Female X Drop out	0.392	(0.032)
High School Program (Benchmark = General Track - Humanities & Social Sciences)		
General Track - Sciences X Wait	0.538	(0.248)
General Track - Sciences X Drop out	0.712	(0.238)
Technological Track X Wait	-0.007	(0.299)
Technological Track X Drop out	0.670	(0.271)
Vocational Track X Wait	-0.239	(0.384)
Vocational Track X Drop out	0.670	(0.271)
GPA (Benchmark = General Track - Humanities & Social Sciences)		
GPA X Wait	0.076	(0.016)
GPA X Drop out	-0.030	(0.015)
General Track - Sciences X GPA X Wait	-0.047	(0.022)
General Track - Sciences X GPA X Drop out	-0.139	(0.021)
Technological Track X GPA X Wait	-0.022	(0.027)
Technological Track X GPA X Drop out	-0.089	(0.024)
Vocational Track X GPA X Wait	-0.021	(0.032)
Vocational Track X GPA X Drop out	-0.051	(0.029)
Unobserved Heterogeneity (benchmark = Type 1)		
Type 2 X Wait	0.159	(0.034)
Type 2 X Drop out	0.174	(0.032)

Standard errors in parentheses.

Figure 3: Waiting costs by SES



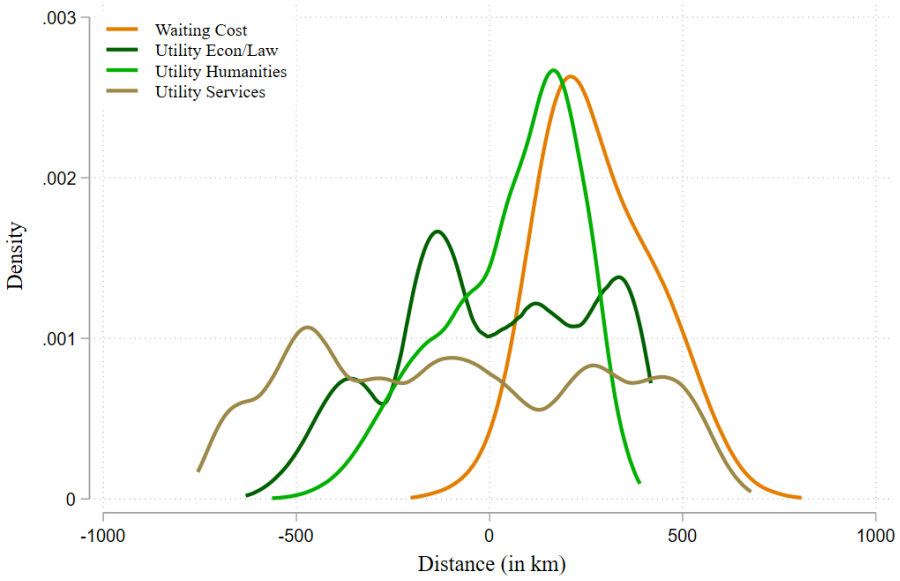
6.4 Benefits of a multi-round mechanism

Multi-round mechanisms have the flexibility to allow seats to open up after students decide to drop out. However, they can also affect the final match through the frictions it imposes. Substantial waiting costs can force students to accept a sub-optimal offer early. Certain characteristics (such as distance) can make this more likely because of housing considerations. At the same time, the trade-off between incurring waiting costs today, against a potentially better offer in the future incorporates the strength of agent preferences in the matching mechanism, potentially leading to increased efficiency. The overall welfare impact of running a sequential mechanism, as well as its distributional effects, is therefore an empirical question.

To answer this question, we simulate both the single-round and the multi-round mechanism and compare the effects on student welfare. Specifically, for the multi-round mechanism, we compute the value for a student of accepting immediately an offer, delaying, or dropping-out. In the counterfactual single-round scenario, we remove the option to delay at the end of the first round.[18] In that scenario, after receiving their first-round assignment, students can

[18]Note that under the assumption that students report their preferences truthfully when submitting their ROLs, the ROL-submission stage is not affected by the presence or the absence of multiple assignment rounds and a future option to delay.

Figure 4: Waiting costs and preferences for types of programs and fields of study



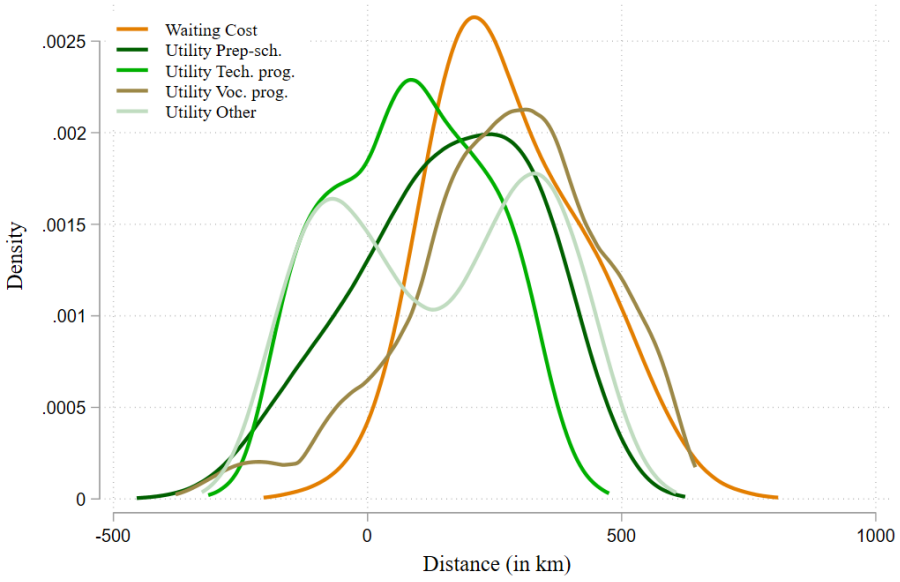


Table 13: Average welfare gains from a multi-round procedure relative to single-round

	Unconditional average		Conditional on not receiving a first-round offer from one's top-ranked program	
	Km-equiv. terms[1]	Relative terms[2]	Km-equiv. terms	Relative terms
Overall	262	0.17	579	0.39
By SES				
High	288	0.18	605	0.40
Medium-high	261	0.16	596	0.39
Medium-low	252	0.16	566	0.40
Low	236	0.15	541	0.38

[1] Equivalent reduction is travel distance, all other things equal. [2] Relative welfare gain is with respect to the welfare created by a single-round mechanism over the outside option —in distance-equivalent terms a reduction of 1,578 km (1,472 km) on average (and conditional on not receiving a first-round offer from one's top-ranked program), and for each of the four SES groups from highest to lowest: 1,570 km; 1,643 km; 1,549 km; 1,578 km (1,507 km; 1,530 km; 1,428 km; and 1,433 km, respectively).

only choose to either accept their current offer or drop out of the platform. Students with no offer in the first round get the utility from dropping out from the platform; students who accept their offer benefit from the early acceptance advantage.

Results are summarized in Table 13. On average, the multi-round procedure provides a gain equivalent to enrolling 262 kilometers closer to home relative to the single-round procedure. Gains from multiple rounds are heterogeneous across SES groups. Higher-SES groups welfare gains equivalent to a reduction in distance from home of 261 to 288 kilometers, against 236–252 for lower-SES groups. To better assess the effect of introducing multiple rounds on welfare inequalities, we renormalize utilities so that the outside option is equivalent to 0 utility and utility estimates capture the value of being assigned on the platform relative to the outside option. The utility difference is substantial for all groups, but especially for the high SES who see an increase of 18%, while the lowest SES group has an increase of 15%. Note that these numbers ignore the fact that for many students, the multi- or single round mechanism is equivalent because they immediately receive their first-ranked offer. If we restrict the sample to the ones that do not (capturing 38% of the population), we see gains that are twice as high.

We also assess how the multi-round mechanism leads to different program types and majors. Table 14 summarizes the results for the group that does not receive their first ranked

offer in Round 1, which can be compared to the status quo (i.e. multi-round) allocation in Table 15. We see a substantial decrease in the number of number of unmatched students, from 29% to 18%. There is an increase in matches for all types of programs, but particularly so for the more specialized ones (prep-school, vocational and technical). For majors, we see particularly more STEM and Services. Finally, we also report the increase in the rank of the accepted offer for this group of affected students. They see the average rank of their program improve substantially, from 4.15 to 3.60.

Table 14: Counterfactual results for students not getting first-ranked offer

Program type	
Bachelor	0.29
Prep-sch.	0.11
Tech. prog.	0.08
Voc. prog.	0.17
Other undergraduate	0.05
Unmatched	0.29
Program major	
STEM	0.19
EconLaw	0.12
Human	0.13
Production	0.10
Services	0.17
Unmatched	0.29
Location	
Distance in 100 km	0.73 (1.19)
City	0.61
Rent in city (100 EUR/month)	4.65 (1.32)
Matching	
Rank of accepted offer	4.15 (2.99)
Welfare	
Welfare gain multi-round (km)	579
Relative welfare gain*	0.39

Average statistics of the counterfactual match with standard deviation in parentheses.
*Relative welfare gain is with respect to the welfare a one round mechanism creates over the outside option: 1,472 km.

Table 15: Status quo for students not getting first-ranked offer

Program type	
Bachelor	0.30
Prep-sch.	0.13
Tech. prog.	0.11
Voc. prog.	0.22
Other undergraduate	0.06
Unmatched	0.18
Program major	
STEM	0.21
EconLaw	0.13
Human	0.14
Production	0.12
Services	0.22
Unmatched	0.18
Location	
Distance in 100 km	0.72 (1.19)
City	0.61
Rent in city (100 EUR/month)	4.73 (1.36)
Matching	
Rank of accepted offer	3.60 (2.77)

Average statistics of the status quo match with standard deviation in parentheses.

Appendix Table A-2 and Appendix A-3 break-down these results for different SES categories, showing that changes are happening for all groups, with high SES increasing their participation in prep school, while low SES increase their participation in vocational and technical schools.

7 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 gains for students of all socio-economic groups. Nevertheless, the gains are larger for the high SES students. While multi-round systems can improve outcomes, 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.

Our descriptive analysis on higher education enrollment and graduation suggests that gains extend beyond the initial match outcome. Therefore, we are currently extending our model with these data such that we can quantify the impact of a sequential mechanism after the match has taken place.

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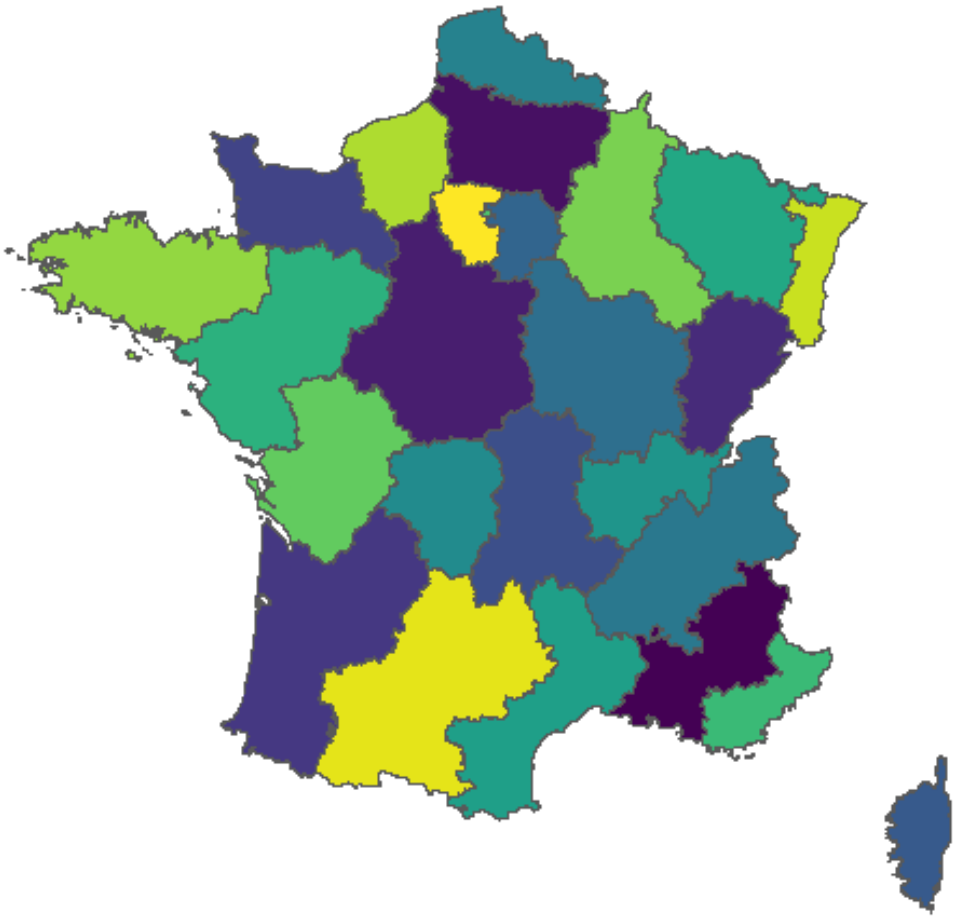
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A Data appendix

Academic regions. Figure A-1 shows the regions used by Bachelor programs to determine coarse priority groups.

Figure A-1: Academic regions in France



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 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.

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.

A.1 Sample description

Table A-1: Sample Description

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
High-school major	
Sciences major	0.54
Social sciences major	0.31
Humanities major	0.15
High-School GPA	
High-School GPA - General Track	11.61
High-School GPA - Technical Track	11.10
High-School GPA - Vocational Track	12.13
Applications and offers	
Average number of programs listed	6.61
Average rank of Round-1 offer	2.22
Average rank of accepted offer	1.98
Share Round-1 offer outside of rank 1	0.38
Matched Program	
Bachelor program	0.48
Prep-school program	0.10
Technical program	0.12
Vocational program	0.22
Other program	0.07
STEM major	0.29
Econ./Law major	0.14
Humanities major	0.19
Production	0.13
Services	0.24
Distance (in 100km)	0.599
Urban location (Main city)	0.64
Monthly rent (cond. on urban location, in 100euros)	0.459
Observations	426852

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

Table A-2: Counterfactual results for students not getting first-ranked offer by SES

SES	High	Med.-high	Med.-low	Low
Program type				
Bachelor	0.28	0.31	0.29	0.30
Prep-sch.	0.20	0.10	0.07	0.05
Tech. prog.	0.08	0.09	0.09	0.07
Voc. prog.	0.09	0.17	0.21	0.25
Other undergraduate	0.08	0.05	0.04	0.02
Unmatched	0.27	0.27	0.30	0.30
Program major				
STEM	0.26	0.19	0.15	0.13
EconLaw	0.15	0.10	0.11	0.11
Human	0.13	0.15	0.12	0.12
Production	0.07	0.11	0.11	0.11
Services	0.11	0.17	0.21	0.23
Unmatched	0.27	0.27	0.30	0.30
Location				
Distance in 100 km	0.83	0.76	0.71	0.55
	(1.34)	(1.2)	(1.15)	(.92)
City	0.65	0.62	0.58	0.57
Rent in city (100 EUR/month)	4.90	4.48	4.53	4.48
	(1.44)	(1.24)	(1.23)	(1.2)
Matching				
Rank of accepted offer	4.48	3.94	4.03	3.93
	(3.29)	(2.74)	(2.8)	(2.84)
Welfare				
Welfare gain multi-round (km)	605	596	566	541
Relative welfare gain*	0.40	0.39	0.40	0.38

Average statistics of the counterfactual match with standard deviation in parentheses.
*Relative welfare gain is with respect to the welfare a one round mechanism creates over the outside option, resp. : 1,507 km, 1,530 km, 1,428 km, 1,433 km.

Table A-3: Status quo for students not getting first-ranked offer by SES

SES	High	Med.-high	Med.-low	Low
Program type				
Bachelor	0.28	0.32	0.30	0.32
Prep-sch.	0.23	0.11	0.08	0.05
Tech. prog.	0.10	0.12	0.12	0.10
Voc. prog.	0.11	0.22	0.27	0.32
Other undergraduate	0.09	0.07	0.05	0.03
Unmatched	0.19	0.15	0.18	0.18
Program major				
STEM	0.30	0.22	0.17	0.14
EconLaw	0.16	0.10	0.12	0.12
Human	0.14	0.16	0.13	0.13
Production	0.09	0.14	0.13	0.14
Services	0.13	0.22	0.27	0.30
Unmatched	0.19	0.15	0.18	0.18
Location				
Distance in 100 km	0.84	0.76	0.69	0.52
	(1.36)	(1.22)	(1.14)	(.88)
City	0.65	0.62	0.58	0.56
Rent in city (100 EUR/month)	4.98	4.55	4.60	4.58
	(1.46)	(1.28)	(1.28)	(1.28)
Matching				
Rank of accepted offer	3.88	3.46	3.47	3.42
	(3.04)	(2.55)	(2.57)	(2.72)

Average statistics of the status quo match with standard deviation in parentheses.