College Admission Mechanisms and the Opportunity Cost of Time*

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April 12, 2023

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 and its distributional consequences in a setting in which waiting costs can be heterogeneous across socio-economic groups. To do so, we use administrative data on rank-ordered lists and waiting decisions from the French college admission system to estimate a dynamic model of application decisions. We find that waiting costs are a key determinant of the timing of students' acceptance decisions and of their final assignment. Nevertheless, we find substantial, but unequal, welfare gains from using a multi-round system.

*Preliminary version. We thank Pierre Dubois, Thierry Magnac, Chris Taber and seminar participants at the Toulouse School of Economics, 2022 IAAE, IWAEE and ESEM conferences for useful comments and suggestions. Olivier De Groote and Anaïs Fabre acknowledge funding from the French National Research Agency (ANR) under the Investments for the Future (Investissements d'Avenir) program, grant ANR-17-EURE-0010. We also acknowledge funding from the ANR grant MATCHINEQ - ANR-22-CE26-0005-01.

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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 (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., 2020). 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 thus 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.

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 their choices to accept, delay or drop out within a dynamic framework. Detailed information on ROLs and choices in the different rounds allows us to account for both observed and unobserved student heterogeneity. We propose a tractable estimation method by adapting the Conditional Choice Probability (CCP) approach to our context (Arcidiacono & Miller, 2011).

Estimated preferences for programs and waiting costs can be used in counterfactual exercises to explore the distributional consequences of waiting costs, and the welfare effects of sequential procedures. First, 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 sequential information revelation, between increased match quality and heterogeneous costs of waiting. Second, counterfactual simulations of applications and assignments under a sequential procedure where low-SES students' waiting costs are assumed to be equal to the high-SES students' costs provide an estimate of the welfare gains that could be generated by companion policies aimed at decreasing waiting costs for low-SES students — for instance, guaranteeing the availability of affordable housing for students accepting later-round offers.

We obtain three main results. First, while students do prefer nearby college programs, being able to accept the offer early strongly reduces that effect. Second, low-SES students incur large costs of waiting. These costs are of a similar magnitude as the utility differences between colleges, thereby causing sub-optimal matches. These findings may reflect difficulties in finding affordable housing. Third, despite the aforementioned frictions, all groups benefit from a sequential matching mechanism, compared to a one-round mechanism. On average, the current sequential system provides a gain equivalent to enrolling 308 kilometers closer to home. However, the gains are not equally distributed. High SES students gain the equivalent of 343 kilometers, while low SES students experience a somewhat smaller gain, equivalent to 268 kilometers.

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

Related literature. A couple of other recent studies have investigated the properties of sequential assignment mechanisms, that is, mechanisms in which applicants are brought to interact multiple times with the clearinghouse (Bó & Hakimov, 2016; Luflade, 2018; Chen & Pereyra, 2019; Grenet et al., 2019). By focusing on the timing of offer acceptance, our paper is closest to Grenet et al. (2019), who find that students seem more likely to accept early offers in the German admission system, and argue that such behavior can be explained by the fact that students' preferences are not fixed, while learning about them is costly. Unlike this paper we explore an alternative explanation to this phenomenon that relies on waiting costs, and 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.

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

(2020), who study the welfare impacts of off-platform options in Chile, together with the presence of aftermarket frictions generated by the decentralized system of waitlists. They quantify the welfare cost of the presence of off-platform options through a counterfactual scenario where additional programs are added to the platform. While this counterfactual scenario can be understood as a first-best solution, it might be difficult in practice to incentivize programs to join the centralized platform.[2] In contrast, we focus in this paper on the evaluation of mechanisms with sequential rounds as an easy-to-implement solution aimed at mitigating the cost of off-platform options.

More broadly, and beyond the school choice setting, this paper adds to a small but growing set of papers modeling the dynamic considerations induced by centralized assignment mechanisms (Agarwal et al., 2021; Waldinger, 2021; Larroucau & Ríos, 2021). 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.

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]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.

2 The French Higher Education System and the College Admission Procedure

2.1 The French Higher Education System

Education in France is organized in a centralized manner, with primary, secondary and higher education being regulated by the Ministry of Education. It is organized through 30 catchment areas, called *Académies*.[3] Each catchment area is responsible for organizing and administering educational policies within its area, following the directives of the Ministry of Education.

At the start of secondary education, all students choose between three main tracks: general, technological, vocational. This track determines the centralized exam they will take at the end of the three-year secondary education period: the *Baccalauréat Général*, the *Baccalauréat Technologique*, or the *Baccalauréat Professionnel*. Within the tracks, they can also follow different programs. In the general track, they take the form of "Sciences", "Social sciences" and "Humanities".

After this exam, students can choose to pursue their education by enrolling in a higher education program. The French higher education system is highly segregated, and divided into selective and non-selective programs. Non-selective programs correspond to the programs offered by universities, which are prevented from selecting which students to admit based on their academic credentials. These are called the "License" programs and attract a little more than half of the students. In contrast, selective programs are allowed to select candidates, and do not have to disclose the criteria they use to rank applicants.

Selective programs are themselves highly heterogeneous and include:

- CPGE (*Classes Préparatoires aux Grandes Ecoles*). These are two-year preparatory course programs, preparing students to take the competitive exams for admission to the *Grandes Ecoles*, highly selective and public and private institutions.

- DUT (*Diplôme Universitaire de Technologie*). These are two-year technology-oriented programs, offered by the university-based IUT (institutes of technology). Their goal is to train mid-level technical workers, but they also allow students to pursue their education in a *Licence Professionelle*, the university or an engeneering or business school.

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

- BTS (*Brevet de Technicien Supérieur*). These are two-year vocational programs, offered by high-schools. After these two years, students can decide to join the labor force or can enroll in a more advanced degree, most often a *Licence Professionelle*.
- Engineering and Business schools.

The track chosen by students at the start of their secondary education does not formally restrict the higher education choices that they can make at the time they apply: all students can apply to any type of higher education program. In fact, universities are legally prevented from selecting students based on the track they followed in high-school. However, selective programs are allowed to do so. Overall, students' track choices are then strongly correlated with their higher education choices, with students in the general track enrolling mostly in university programs, DUT and CPGE. Students in the technological track enroll mostly in DUT or BTS, and students in the vocational track in BTS.

Students immediately choose a college major upon entry. We aggregate these in the following categories: STEM, economics and law (EconLaw), humanities (Human), Production and Services.

2.2 The Centralized College Admission Mechanism

Since 2009, the application and admission procedures of about 15,000 higher education programs are centralized on an online platform, Admission Post-Bac (APB). Every year, roughly 600,000 students register on the platform. They can start accessing it in January, and have until the end of March to submit their rank-ordered lists, but can modify their rankings up to the end of May. Some restrictions are imposed with respect to the number of programs which can be ranked: in 2015, a student was allowed to rank up to 36 programs, with a maximum of 12 per type of program (Licences, CPGE, DUT, BTS).

Applicants are ranked by selective programs based on the information their high-school and themselves submit on the platform. In contrast, a pre-specified ranking algorithm ranks applicants to non-selective programs. This ranking is based on the student's catchment area and, until 2017, on the absolute rank of the program in the ROL. A lottery number differentiates students in the same priority group. Note that many non-selective programs have enough seats for all applicants, such that this ranking is just a mechanical requirement for the assignment algorithm to be able to run, but does not have real implications for applicants. A subset of non-selective programs are however often over-subscribed. These are usually the medicine (=*PACES*), sports (=*STAPS*), psychology and law programs. In many of these programs, the number of students in the top priority group (the program they ranked at the top of their ROL being in the same catchment area as where they live) is larger than the number of seats offered, making the lottery number instrumental in determining the admission outcome.

Both students' ROL and programs' ranking of applicants are the inputs of a college-proposing Deferred-Acceptance algorithm, the outcome of which matches each student to a program. In contrast to static assignment mechanisms, the APB system is dynamic and allows students to re-match in cases where programs they prefer become available on the platform. This happens when other students choose to reject the offer they received and leave the platform. During each round, each student receives a unique offer. They then have a few days in order to submit their answer, among the three following options [4]:

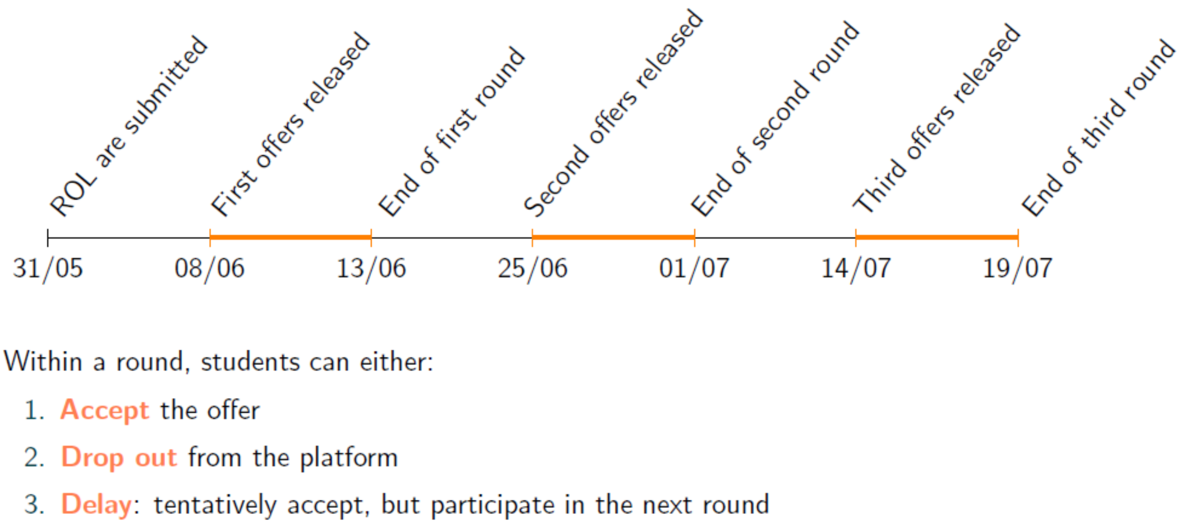
- Accept: the student chooses to immediately accept the offer received, and can proceed with the rest of the enrolment procedure.
- Delay: the student conditionally accepts the offer, but asks for her applications to programs she ranked higher than her pending offer to be considered in the next round. In the next round, the student will again receive a unique offer: either she receives a different offer, from a program ranked higher in her ROL, or she receives the same offer as in the previous round. The student is thus guaranteed to receive an offer in the next round.
- Drop out: the student rejects her offer and leaves the platform.

The APB sequential mechanism contains three rounds, allowing students to receive up to three different offers. For 2015, the timing can be found in Figure 1.

During the last round, up to 2017, students are not able to delay their answer anymore, and thus have to choose between accepting the offer they receive or dropping out from the platform. Similarly, students who receive an offer to their top-ranked choice can only decide whether to accept or reject it. In 2017, students were allowed again to use any of the three options in the third round, in order to maintain their applications throughout an additional round (=*Procédure Complémentaire*). The latter allows programs which still have some seats available to offer them

[4] In practice there was also a fourth option where students rejected the offer and still participated in the next round. As this is difficult to rationalize and only a small number of students used this option we exclude it from the analysis

Figure 1: Timing APB in 2015



to students who did not receive any offer throughout the main procedure, or rejected the offer(s) received.

3 Data and Descriptive Evidence: Students and the Decision of Delaying their Decisions

3.1 Description of the Data

For each year between 2014 and 2017, we have data covering the universe of applicants to the APB platform. In particular, we observe students' characteristics, including their gender, to which SES group they belong,[5] their ZIP code, their high-school track, program, and the grade (=*Mention*) they received at the centralized exam (=*Baccalauréat*). We also have access to the full ROL students submit on the platform, together with details about programs where they apply, including the type (Licence, CPGE, BTS, DUT or other) and the major of the program, as well as its location.

Importantly, we also observe the sequential offers that students receive on the platform across the different admission rounds, as well as students' responses to these offers. We thus observe

[5]We follow the same definition as the French Ministry of Education to define SES groups. The classification is defined based on the socio-professional category of the student's 'legal guardian', that we observe in our data, and consists in four categories: 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).

whether, within a giving round, the student chose to accept, delay, or drop out.

In what follows, we start by providing descriptive evidence regarding students' acceptance behavior on the platform. For that, we use data from 2015 to 2017, and we focus on students in high-school in the year when they apply.

The structural model is estimated on a subsample of this dataset. We restrict attention to the 2015 application process, and focus on students who were in the general high-school track that year, and obtained a passing grade at the end-of-high-school exam. We exclude students studying in the DOM-TOM and abroad. We randomly draw 25% of the students from this sample. To estimate students' preferences over programs, we further restrict the sample by randomly drawing 25% of the students. A detailed overview of the source data can be found in the appendix.

3.2 Motivating evidence

Our analysis focuses on the 2015 cohort, in which we observe 570,866 applicants who submitted 6.5 applications on average. 88 % of them received an offer and 77 % accepted one.

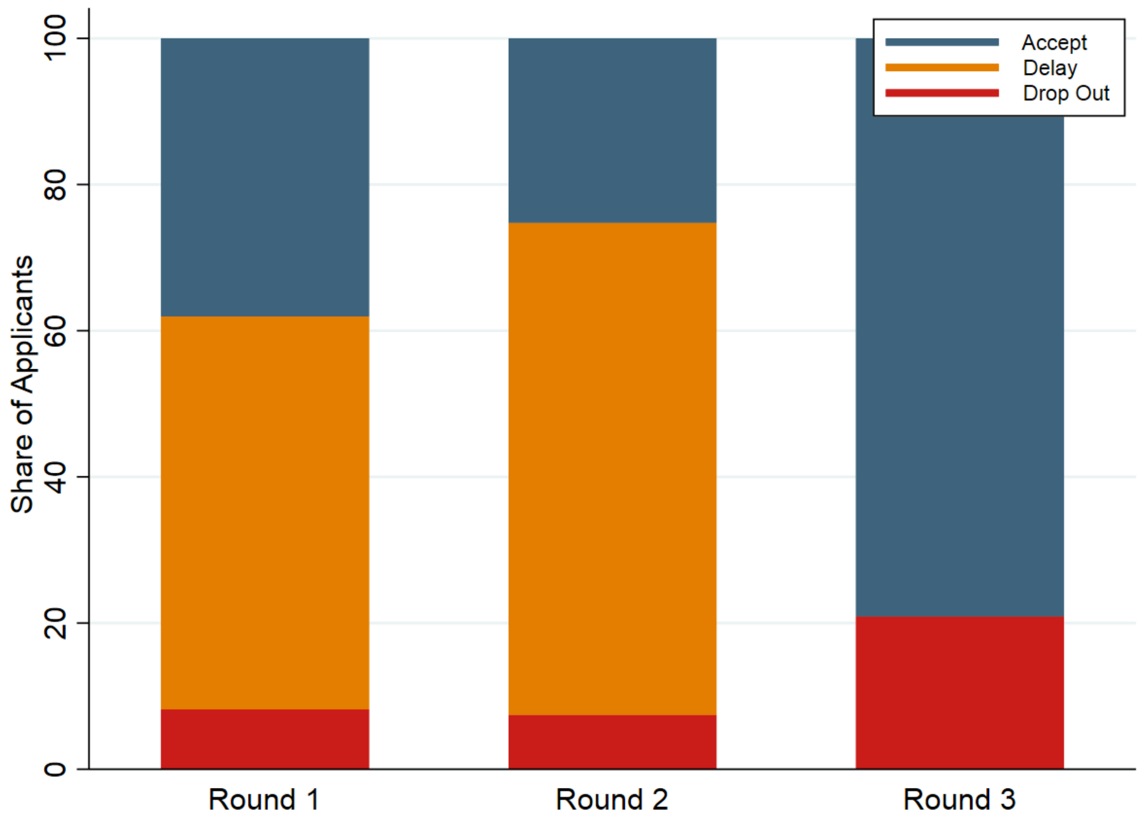
Figure 2 plots the decision of students who received an offer outside the top-ranked program, separately for each round. It shows that almost 40 % decides not to wait for a better option and instead accept it in round 1. Of those that make it to the second round, still more than 20 % decides not to wait until the last round. We also see several students dropping out of the system, thereby making seats available for the students that do decide to wait for better opportunities.

The decision to delay is not distributed equally. Table 1 shows that high SES students are much more likely to choose the option to delay. To explore this further, we also show the average marginal effects of several student characteristics in a logit regression in Figure 3. Apart from SES, also female students, students with a scholarship and students who prefer a program far away are less likely to delay their choice.

The mechanism allows students to receive better offers. 20 % of the students delaying in round 1 receive a better offer in round 2 and 25 % of the students delaying in round 1 and 2 receive a better offer in round 3.

These results suggest that students experience non-trivial costs to wait for their final match. This is particularly the case for low SES students and for students that want to match to an option far away, suggesting that difficulties in finding affordable housing could play a role. However, these students might not only differ in the cost of waiting. The gain could also be different as it depends

Figure 2: Decision in different rounds of APB in 2015

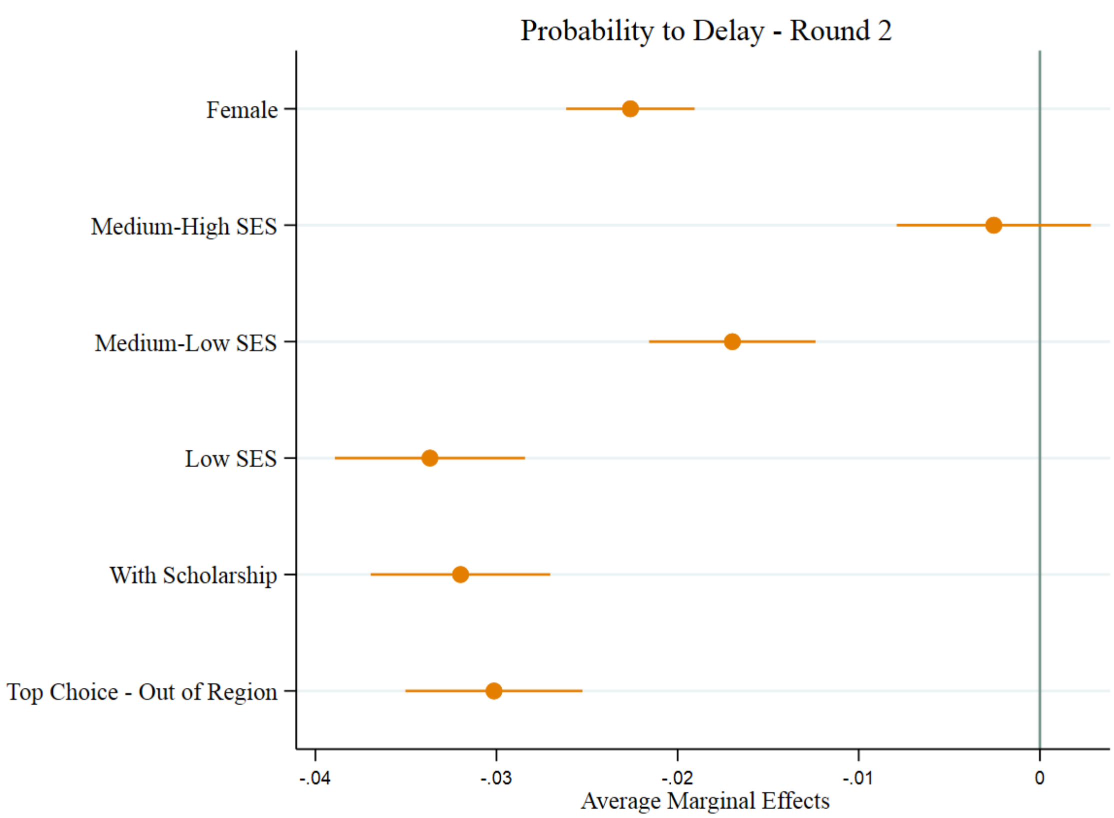


on the difference in utility of the higher ranked alternatives and the probability to receive an offer in future rounds. Our structural model will explicitly control for this option value in estimating the waiting costs that students experience.

Table 1: % of students who received an offer outside their top-ranked program using delaying option

	(1) High SES	(2) Medium-High SES	(3) Medium-Low SES	(4) Low SES
		Round 1		
Percentage	56.56	55.49	53.84	49.48
		Round 2		
Percentage	67.27	65.73	63.62	60.84

Figure 3: Average marginal effects of deciding to delay in round 2 of APB in 2015



3.3 Estimation Sample

The structural model is estimated on a subsample of this dataset. We restrict attention to the 2015 application process, and focus on students who were in the general high-school track that year, and obtained a passing grade at the end-of-high-school exam. We exclude students studying in the DOM-TOM and abroad. We randomly draw 25% of the students from this sample. To estimate students' preferences over programs, we further restrict the sample by randomly drawing 25% of the students. Table 2 presents descriptive statistics of the students in the sample. Table 3 shows to what type of programs these students are admitted.

Table 2: Descriptive Statistics - Students

Female	0.57
High	0.40
Medium-High	0.16
Medium-Low	0.27
Low	0.17
With scholarship	0.13
Very Good	0.12
Good	0.19
Sufficiently Good	0.28
Sufficient	0.40
Sciences	0.54
Social Sciences	0.31
Humanities	0.15
Rank - Offer Round 1	2.19
Number Applications	7.09
Rank - Admission	1.95
Observations	67,425

A detailed overview of the source data can be found in the appendix.

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 different answers available on the platform.

Table 3: Descriptive Statistics - Students

Admitted: Licence	0.52
Admitted: CPGE	0.12
Admitted: DUT	0.10
Admitted: BTS	0.05
Admitted: Other	0.07
Admitted: None	0.14
Admitted: STEM	0.33
Admitted: EconLaw	0.16
Admitted: Human	0.20
Admitted: Production	0.06
Admitted: Services	0.11
Admitted: None	0.14
Admitted: Licence X STEM	0.21
Admitted: Licence X EconLaw	0.13
Admitted: Licence X Human	0.18
Admitted: Licence X Production	0.00
Admitted: Licence X Services	0.00
Admitted: CPGE X STEM	0.07
Admitted: CPGE X EconLaw	0.03
Admitted: CPGE X Human	0.02
Admitted: CPGE X Production	0.00
Admitted: CPGE X Services	0.00
Admitted: DUT X STEM	0.00
Admitted: DUT X EconLaw	0.00
Admitted: DUT X Human	0.00
Admitted: DUT X Productio	0.05
Admitted: DUT X Services	0.05
Admitted: BTS X STEM	0.00
Admitted: BTS X EconLaw	0.00
Admitted: BTS X Human	0.00
Admitted: BTS X Productio	0.04
Admitted: BTS X Services	0.01
Admitted: Other X STEM	0.05
Admitted: Other X EconLaw	0.00
Admitted: Other X Human	0.01
Admitted: Other X Productio	0.02
Admitted: Other X Services	0.00
Observations	67,425

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. Students are recommended to rank programs according to their preferences, and we will assume they do.

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 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 Under the truth-telling assumption, students form their ROL by choosing a program j for rank $r \in \{1, ..., \bar{R}\}$ of their ROL, denoted d_{ir}^{ROL}, with $\bar{R}$ being the maximum length of the list. Assuming an extreme value type 1 distribution on η_{ij} with scale parameter σ, we obtain the well-known exploded (or rank-ordered) logit probabilities:

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

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 $\mathcal{J}$.

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 $j_t \neq 0$, they can choose between options $k = \{1, 2, 3\}$ to maximize their expected lifetime utility. They denote respectively accepting the offer, delaying the decision, or dropping out from the platform. If $j_t = 0$, only $k = 2$ and $k = 3$ are available. 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 ($e_{j_t,t}(S_i, \tau)$):

$$v_{i1t} = u_{j_t}(S_i, \tau) + e_{j_t}(S_i, \tau) \times I(t < 3) \tag{2}$$

with $I()$ the indicator function. The early acceptance advantage allows for deviations from the utility at enrollment to take into account that some students might prefer to know the characteristics of their program sufficiently in advance. More specifically, we expect housing opportunities to differ and will therefore estimate how distance and local rents affect this advantage.

Delay ($k = 2$) A student can also decide to wait for better options, while not losing the currently assigned alternative. In this case, they incur a waiting cost in the current period: $\omega_{it} = \omega_t(S_i, \tau)$. In contrast to the early acceptance advantage, this captures the impatience of students that is unrelated to the characteristics of the offer. This baseline cost of waiting can be financial. Low-SES households in particular could benefit from knowing that the student will enroll to prepare for the cost of studying. It could also be psychic costs: high if the student is impatient, low (and even negative) if they procrastinate. In addition to waiting costs, students also receive a continuation value that captures their (weakly) improved offer in the next round. The conditional value function is then given by:

$$v_{i2t} = -\omega_t(S_i, \tau) + \sum_{j' \in \mathcal{R}_i^{j_t} \cup \{j_t\}} \Pr(j_{t+1} = j' | \Omega_{it}) \bar{V}_{it+1}(\Omega_{it}, j_{t+1}) \tag{3}$$

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:

$$\Omega_{it} = (S_i, \tau, \mathcal{R}_i, t, j_t). \tag{4}$$

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

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

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

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

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

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

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

Substituting this in (3), 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.

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 if 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 License-STEM program with other characteristics (such as distance) set to 0.

Scale and dropout in terminal period Given the program utility, we can identify dropout utility in the last period ($t = 3$). To see this, note that in $t = 3$, there is no early acceptance advantage in v_{i1t} and there is no possibility to choose $k = 2$. Therefore, we obtain a static model with the utility of $k = 1$ known up to scale parameter σ, and dropout utility identified from the observed accept/dropout decision. We first identify the scale. Calculate choice probabilities in $t = 3$ and map them into utility functions:

$$\begin{aligned} \ln \Pr(d_{i3}^{DDC} = 1 | \Omega_{i3}) - \ln \Pr(d_{i3}^{DDC} = 3 | \Omega_{i3}) &= v_{i13} - v_{i33} \\ &= u_{j_3}(S_i, \tau) - u_{03}(S_i, \tau) \\ &= \sigma \tilde{u}_{j_3}(S_i, \tau) - u_{03}(S_i, \tau). \end{aligned} \tag{8}$$

with Ω_{it} given by (4) and the conditional value functions by (2) and (5). Let z be a program characteristic with $\frac{\partial \tilde{u}_{j_3}(S_i,\tau)}{\partial z} \neq 0$. As z is excluded from u_{0t}, taking derivatives and re-arranging yields the scale parameter:

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

With probabilities observed and $\frac{\partial \tilde{u}_{j_3}(S_i,\tau)}{\partial z}$ identified from the ROL, we have identified the scale, and therefore also $u_{j_3}(S_i, \tau)$. We can use (8) again to identify the utility of drop out $u_{03}(S_i, \tau)$.

Other primitives in the dynamic model While state transitions are identified nonparametrically, utilities 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 an alternative in each state (Magnac & Thesmar (2002)).

We assume a mean-zero extreme value type 1 distribution on the taste shocks and we normalize the discount factor to 1 (as different stages follow each other quickly). If the early acceptance advantage $e_{j_t}(S_i, \tau)$ was known, we would be in the standard case, with the utility of $k = 1$ known in every state. To identify the early acceptance advantage, we again exploit the program characteristics of the assigned alternative j_t. While student characteristics drive waiting costs and dropout utility, we set their baseline effect on the early acceptance advantage to be 0. Baseline effects of program characteristics of j_t, as well as their interactions with student characteristics, are identified as they do not enter waiting costs and dropout utility. 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.

Unobserved types Both the ROL and the panel data of the dynamic model identify the unobserved types as only types are able to capture unobserved heterogeneity that is correlated within a ROL and between periods. For example, if students that rank License programs in rank 1 also usually put a License program in rank 2, it indicates the existence of an unobserved type that prefers License programs. Students that repeatedly delay their decision, despite a good j_t, suggest a low waiting cost type.

5.2 Parameterization

To obtain efficient estimates from our sample, we impose the following parametric structure.

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

$$u_j(S_i, \tau) = X'_{ij}(\Lambda S_i + \lambda_\tau) \text{ for } j \neq 0 \tag{9}$$

X_{ij} is a $K \times 1$ vector of observed program characteristics. Λ is a $K \times L$ matrix of parameters capturing the impact of observed student characteristics on program characteristics.[6] λ_τ is a $K \times 1$ vector of parameters capturing the impact of an unobserved student type.

A first set of program characteristics captures indicator variables for each program type and major. Since only differences in utility are identified, we estimate the difference with a License program, in a STEM major, by including indicator variables for types (CPGE, BTS, DUT, other) and major (Econ/Law, Humanities, Services, Production). A second set of characteristics flexibly captures the location characteristics. We include measures relative to the location of the students such as distance from home and indicators for the same catchment area and region.[7] We also include proxies for local housing costs by distinguishing between programs inside and outside cities. For programs in cities, we further distinguish by measures of local rents. Finally, for CPGE programs, we include indicators for dorms being available.

The vector of students' characteristics captures the gender of the student, her SES status, her grade at the centralized exam and indicators for each track in high school (Sciences, Humanities, Social Sciences). Type τ captures heterogeneity in preferences that is not explained by these characteristics.

Early acceptance advantage The early acceptance advantage is parameterized in a similar way:

$$e_{j_t}(S_i, \tau) = X'_{ij}(\Phi S_i + \phi_\tau) \tag{10}$$

with Φ and ϕ_τ capturing the impact on the early acceptance advantage of respectively observed and unobserved student characteristics. To keep the model estimation tractable, we include only the program characteristics that capture mobility concerns. We include distance, a dummy for the program being located in a city, and (for cities) the local rent.

Waiting costs and utility of drop out Finally, we specify heterogeneous waiting costs and outside options as follows:

$$\omega_t(S_i, \tau) = \psi_s S_i + \psi_\tau + \psi_t \tag{11}$$

[6] We observe K program characteristics and $L - 1$ student characteristics because we include a dummy in S_i to capture the baseline effect of program characteristics.

[7] Regions correspond to the geographic administrative units called *Département* in France. There are 96 such regions in metropolitan France.

$$u_{0t}(S_i, \tau) = \alpha_s S_i + \alpha_\tau + \alpha_t \text{ for } j = 0 \tag{12}$$

with the shifts of intercepts for the first type and period normalized to 0. Note also that $\omega_t(S_i, \tau)$ is only defined for $t < 3$.

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 (4). We consider a parametric, but flexible relation by estimating a logit model that predicts the probability to improve the 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 is also allowed to affect this, and we allow for heterogeneous effects by S_i and τ. Finally, we control for dorm availability and the rank of the current offer, and we add controls for the number of higher-ranked programs in the ROL of each type and each major. For the conditional logit, we first predict a program's selectivity.[8] This index enters with a round-specific effect. Furthermore, we include a dummy for living in the catchment area of the program, the rank, major and type. We also allow the latter to depend on being inside or outside the catchment area.

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 $\omega_t(S_i, \tau)$. 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:

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

[8] 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. In order to do this, we only keep 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 DUT and BTS. The EconLaw, STEM and Humanities majors are allowed to have different effects in CPGE, Licence and other programs.

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

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 an exploded logit model on the ROLs.[9] 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.

5.4 CCP estimation

To estimate θ_3, we need to solve the model of stage 2 for each value of the state. This is cumbersome as the state space consists of every option that student i included in its ROL.

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

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

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

[9]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.

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

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

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 and the estimator essentially becomes similar to the estimator of static model with a correction term.[10]

5.5 Estimation with unknown types

Let there be M types τ with probability to occur π_τ. We then obtain the following loglikelihood 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 loglikelihood 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 therefore follow 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.

[10] We predict CCPs 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 and majors. For the characteristics of the current offer, we take into account the same variables that enter the utility function, but also the current rank and selectivity index.

6 Estimation Results & counterfactual simulations

In this section we report all utility estimates.[11] The estimates of state transitions and the CCP are available upon request.

6.1 Program utility

The results on the utility of each program are summarized in Table 4, Table 5 and Table 6. To interpret them well, it is important to note that we report the estimates Λ/σ and λ_τ/σ. To compare them to other utility estimates (waiting costs and drop out), they should be multiplied by the estimate of the scale parameter σ: 0.118 (with standard error of 0.00442). This estimate implies that the standard deviation of the "trembling hand" error in the ROL is quite small as it resembles about 12% of a standard deviation in the taste shocks that enter the dynamic choice model. Note also that several indicator variables enter so we need to choose some benchmarks. For the program characteristics, we use the License program and STEM major as the benchmark. For the student characteristics, we use the male, high SES, high grade, sciences, no scholarship, type 1 student as a benchmark.

The first part of Table 4 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 like proximity. This is reflected in the negative coefficient on distance, as well as in the nonlinear effects coming from staying in the region and 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, the elite program type (CPGE) is valued more than a license program by the benchmark group, equivalent to a decrease in distance of 41 km ($= 100 \times (0.364/0.891) = 40.9$). To capture differences in housing conditions, we allow for different preferences to study in the main cities of France. Furthermore, 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 observe that at 0 rent, students prefer not to live in a city, but they prefer locations where amenities are better. Finally, we control for the program having a dorm available. Students seem to value programs with a dorm available, but do not necessarily submit a dorm application: the presence of dorm could simply

[11] Standard errors do not correct for the uncertainty in estimating unobserved types and the use of predicted values for CCPs and state transitions.

Table 4: Program utility (part 1 of 3)

Common component		
Program type (benchmark = License)		
CPGE	0.364	(0.049)
DUT	-0.174	(0.178)
BTS	-3.774	(0.207)
OTHER	-0.692	(0.072)
Program major (benchmark = STEM)		
EconLaw	-0.220	(0.045)
Human	-2.125	(0.048)
Production	-1.421	(0.188)
Services	-2.172	(0.156)
Same region	0.781	(0.013)
Same catchment area	1.282	(0.014)
Main City	-0.494	(0.022)
Main City X Rent	0.206	(0.004)
Dorm Available	0.189	(0.031)
Dorm Available X Applied Dorm	-0.400	(0.020)
Distance	-0.891	(0.007)
Heterogeneity		
SES Group (benchmark = High SES)		
Medium-High X CPGE	-0.446	(0.043)
Medium-High X DUT	-0.392	(0.101)
Medium-High X BTS	-0.094	(0.102)
Medium-High X Other	-0.464	(0.055)
Medium-Low X CPGE	-0.515	(0.039)
Medium-Low X DUT	-0.917	(0.089)
Medium-Low X BTS	-0.483	(0.090)
Medium-Low X Other	-0.767	(0.052)
Low X CPGE	-0.880	(0.049)
Low X DUT	-1.423	(0.108)
Low X BTS	-0.825	(0.108)
Low X Other	-1.155	(0.067)
Medium-High X EconLaw	-0.425	(0.045)
Medium-High X Human	-0.049	(0.045)
Medium-High X Production	0.400	(0.103)
Medium-High X Services	0.285	(0.095)
Medium-Low X EconLaw	-0.317	(0.039)
Medium-Low X Human	-0.092	(0.040)
Medium-Low X Production	0.994	(0.091)
Medium-Low X Services	0.756	(0.083)
Low X EconLaw	-0.525	(0.047)
Low X Human	-0.334	(0.048)
Low X Production	1.195	(0.108)
Low X Services	0.921	(0.101)
# Students	17,188	

Standard errors in parentheses. Estimation is performed on a random sample of 6% of the applicants enrolled in the general high-school track and living in metropolitan France in 2015.

Table 5: Program utility (part 2 of 3)

Heterogeneity (continued)		
Grade (benchmark = Very Good)		
Good X CPGE	-1.247	(0.043)
Good X DUT	0.063	(0.186)
Good X BTS	0.382	(0.216)
Good X Other	-0.434	(0.062)
Sufficiently Good X CPGE	-2.367	(0.045)
Sufficiently Good X DUT	-0.289	(0.176)
Sufficiently Good X BTS	0.169	(0.205)
Sufficiently Good X Other	-0.964	(0.062)
Sufficient X CPGE	-3.883	(0.051)
Sufficient X DUT	-1.566	(0.174)
Sufficient X BTS	-0.368	(0.202)
Sufficient X Other	-1.860	(0.065)
Good X EconLaw	0.024	(0.049)
Good X Human	-0.170	(0.049)
Good X Production	0.182	(0.197)
Good X Services	0.991	(0.164)
Sufficiently Good X EconLaw	-0.128	(0.048)
Sufficiently Good X Human	-0.406	(0.049)
Sufficiently Good X Production	0.977	(0.186)
Sufficiently Good X Services	1.990	(0.156)
Sufficient X EconLaw	-0.399	(0.047)
Sufficient X Human	-0.568	(0.048)
Sufficient X Production	2.020	(0.183)
Sufficient X Services	3.255	(0.154)
High School Program (benchmark = Sciences)		
Social Sciences X CPGE	-2.240	(0.039)
Social Sciences X DUT	-1.455	(0.085)
Social Sciences X BTS	-1.730	(0.086)
Social Sciences X Other	-2.680	(0.059)
Humanities X CPGE	-1.406	(0.050)
Humanities X DUT	-1.197	(0.142)
Humanities X BTS	-0.570	(0.136)
Humanities X Other	-2.123	(0.065)
Social Sciences X EconLaw	5.547	(0.055)
Social Sciences X Human	3.347	(0.048)
Social Sciences X Production	-0.249	(0.107)
Social Sciences X Services	7.962	(0.096)
Humanities X EconLaw	4.716	(0.088)
Humanities X Human	5.416	(0.082)
Humanities X Production	-0.670	(0.246)
Humanities X Services	5.593	(0.153)
# Students	17,188	

Standard errors in parentheses. Estimation is performed on a random sample of 6% of the applicants enrolled in the general high-school track and living in metropolitan France in 2015.

Table 6: Program utility (part 3 of 3)

Heterogeneity (continued)		
Scholarship Status (benchmark = Without Scholarship)		
With Scholarship X CPGE	0.138	(0.050)
With Scholarship X DUT	0.098	(0.111)
With Scholarship X BTS	0.103	(0.110)
With Scholarship X Other	0.085	(0.069)
With Scholarship X EconLaw	0.006	(0.048)
With Scholarship X Human	-0.111	(0.049)
With Scholarship X Production	-0.203	(0.112)
With Scholarship X Services	-0.391	(0.106)
Sex (benchmark = Female)		
Female X CPGE	-0.227	(0.031)
Female X DUT	-0.954	(0.071)
Female X BTS	-0.625	(0.072)
Female X Other	-0.486	(0.040)
Female X EconLaw	0.223	(0.031)
Female X Human	0.823	(0.032)
Female X Production	0.113	(0.074)
Female X Services	0.877	(0.067)
Unobserved Type (benchmark = Type 1)		
Type 2 X CPGE	3.758	(0.039)
Type 2 X DUT	4.537	(0.105)
Type 2 X BTS	4.143	(0.107)
Type 2 X Other	4.745	(0.062)
Type 2 X EconLaw	-2.866	(0.045)
Type 2 X Human	-0.120	(0.038)
Type 2 X Production	-1.970	(0.105)
Type 2 X Services	-9.315	(0.111)
# Students	17,188	

Standard errors in parentheses. Estimation is performed on a random sample of 6% of the applicants enrolled in the general high-school track and living in metropolitan France in 2015.

signal programs of higher quality.

The rest of Table 4, as well as Tables 5 and 6 describe the heterogeneity in program preferences, i.e. how utilities differ for the students that do not belong to the benchmark group. We can conclude that lower SES or lower grades make students less likely to consider alternatives to the license program. However, this is for the benchmark STEM major. Note that there are no STEM majors in DUT and BTS programs, which contain only production and services majors. Here we do see an increase for lower SES and grades. The majors that are more common elsewhere (EconLaw and Human) are preferred less when SES or grades are lower. Note that we also control for high school scholarship status, but the effects relatively small compared to the SES categories. As expected, a background in the high school social sciences or humanities program make students more likely to consider alternative majors than STEM or production. For the type of program, there is a similar hierarchy as with individual characteristics, with students from non-science programs being less likely to consider non-license programs. Finally, we find strong gender effects with female students less likely to consider alternatives to the license programs, and more likely to study Human or Services, rather than STEM, EconLaw or Production.

Table 6 concludes with the heterogeneity that is not explained by observable characteristics. 47% of the population is estimated to be of unobserved type 2. This type is capturing a much higher willingness to consider alternatives to the license program. For example, the difference in utility derived from the elite CPGE program, is equivalent to moving (or travelling) 422 km closer to home. This type is also significantly less likely to consider a non-STEM major. Despite the rich set of observable characteristics, these results show that it is important to also allow for unobserved heterogeneity in preferences.

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 (Φ and ϕ_τ): Table 7.

Because of housing considerations, accepting a program early in the process can have substantial benefits for students. Table 7 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 0.116 utils. Note that this is very close to the disutility to travel 100 km for a program, which is estimated to be -0.105

Table 7: Utility from early acceptance

Distance - Early Acceptance		
Distance	0.116	(0.023)
Distance X Female	0.013	(0.016)
Distance X Type 2	-0.048	(0.015)
Distance X Medium-High SES	-0.041	(0.022)
Distance X Medium-Low SES	-0.010	(0.019)
Distance X Low SES	-0.053	(0.026)
Distance X With Scholarship	-0.030	(0.025)
Distance X Good	0.010	(0.023)
Distance X Sufficiently Good	-0.003	(0.022)
Distance X Sufficient	0.039	(0.022)
Distance X Social Sciences	-0.025	(0.018)
Distance X Humanities	-0.008	(0.022)
Main City - Early Acceptance		
Main City	0.116	(0.023)
Main City X Female	-0.104	(0.087)
Main City X Type 2	-0.008	(0.084)
Main City X Medium-High SES	0.084	(0.127)
Main City X Medium-Low SES	-0.026	(0.108)
Main City X Low SES	-0.148	(0.134)
Main City X With Scholarship	0.043	(0.137)
Main City X Good	-0.026	(0.147)
Main City X Sufficiently Good	-0.273	(0.140)
Main City X Sufficient	-0.348	(0.135)
Main City X Social Sciences	0.094	(0.095)
Main City X Humanities	-0.234	(0.123)
Main City X Rent - Early Acceptance		
Main City X Rent	-0.006	(0.025)
Main City X Rent X Female	0.028	(0.017)
Main City X Rent X Type 2	-0.020	(0.016)
Main City X Rent X Medium-High SES	-0.006	(0.026)
Main City X Rent X Medium-Low SES	-0.004	(0.021)
Main City X Rent X Low SES	0.014	(0.027)
Main City X Rent X With Scholarship	0.017	(0.027)
Main City X Rent X Good	-0.007	(0.027)
Main City X Rent X Sufficiently Good	0.032	(0.026)
Main City X Rent X Sufficient	0.023	(0.025)
Main City X Rent X Social Sciences	-0.036	(0.019)
Main City X Rent X Humanities	0.031	(0.023)
# Students	67,425	

Standard errors in parentheses. Estimation is performed on a random sample of 25% of the applicants enrolled in the general high-school track and living in metropolitan France in 2015.

($= -0.891 \times 0.118$). We can therefore conclude that early knowledge on where to be admitted can reduce the travel cost entirely for a large group of students (apart from the nonlinear effects coming from living in the same region and catchment areas). Since student background might influence the available housing options, we also allow for heterogeneity in this parameter but we see that the differences in effects are often small and no clear patterns emerge.

Another variable that captures housing considerations is the proxy for local amenities (the city dummy and the change in the city effect by local rents). While the effects for rents are small and insignificant, students are more likely to accept a program located in a city. There is also heterogeneity in the effect, but the results are too imprecise to make strong statements.

6.3 Waiting costs and drop out utility

The waiting costs (ψ) and drop out utility (α) can be found in Table 8. Note that the tables report the negative of the waiting costs parameters (-ψ) so they should be interpreted as utility, rather than disutility.

Drop out captures both colleges that do not participate on the platform, as well as students deciding not to go to college. It is therefore not a priori clear what to expect from the results. We see that the group who derives more utility from dropping out is more likely to be of high SES and without a scholarship. These are characteristics we also saw for people preferring the more elite CPGE program over a license program. However, it is also more likely for students of type 1, female students, students with low grades and students coming from the social sciences and humanities high school programs. These characteristics were associated with participation in license programs.

Waiting for the final outcome is not considered costly for every student. The benchmark student derives some positive utility from waiting, potentially capturing procrastination. For type 2 students it remains positive, but at a lower level. However, there is important heterogeneity that can be explained by high school background. Students who obtained lower grades and come from humanities do experience costs from waiting.

To show the importance of waiting costs, we plot the distribution. We scale the waiting costs in kilometers ($= \psi/(0.00891 \times 0.118)$), and compare it to the utility differences with the STEM major (Figure 4) and with the license program type (Figure 5), which are also scaled in kilometers. We see that waiting costs are positive (i.e. waiting utility is negative) for the majority of students.

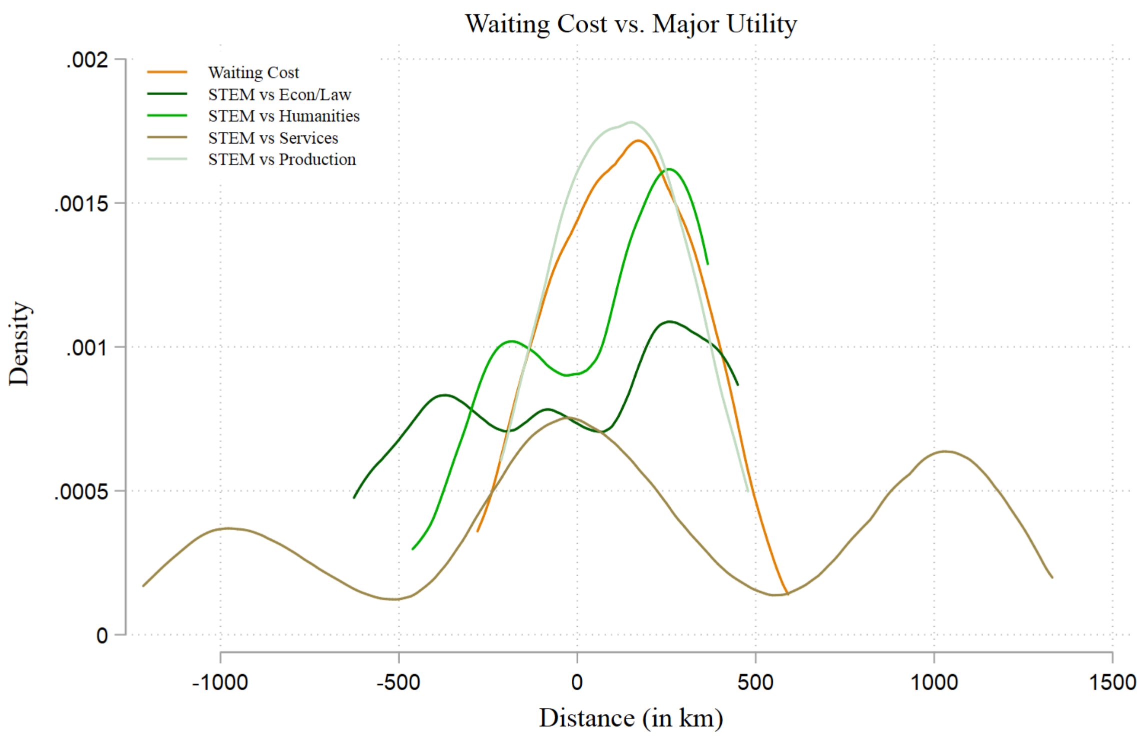
Table 8: Utility from waiting and drop out

Common component		
Wait	0.229	(0.065)
Drop Out X Round 1	-2.299	(0.060)
Drop Out X Round 2	-1.958	(0.063)
Drop Out X Round 3	-1.433	(0.061)
Heterogeneity		
SES Group (benchmark = High SES)		
Medium-High X Wait	0.014	(0.048)
Medium-Low X Wait	-0.023	(0.041)
Low X Wait	0.019	(0.051)
Medium-High X Drop out	-0.328	(0.046)
Medium-Low X Drop out	-0.302	(0.039)
Low X Drop out	-0.568	(0.049)
Scholarship Status (benchmark = Without Scholarship)		
With Scholarship X Wait	-0.039	(0.053)
With Scholarship X Drop out	-0.330	(0.052)
Sex (benchmark = Male)		
Female X Wait	0.025	(0.034)
Female X Drop out	0.244	(0.033)
Grade (benchmark = Very Good)		
Good X Wait	-0.127	(0.064)
Sufficiently Good X Wait	-0.272	(0.060)
Sufficient X Wait	-0.491	(0.058)
Good X Drop out	-0.047	(0.063)
Sufficiently Good X Drop out	0.140	(0.058)
Sufficiently X Drop out	0.340	(0.056)
Unobserved Heterogeneity (benchmark = Type 1)		
Type 2 X Wait	-0.108	(0.033)
Type 2 X Drop out	-0.403	(0.031)
High School Program (benchmark = Sciences)		
Social Sciences X Wait	0.021	(0.036)
Humanities X Wait	-0.191	(0.050)
Social Sciences X Drop out	0.873	(0.037)
Humanities X Drop out	0.816	(0.051)
# Students	67,425	

Standard errors in parentheses. Estimation is performed on a random sample of 25% of the applicants enrolled in the general high-school track and living in metropolitan France in 2015.

The median waiting cost corresponds to 141 kilometers, implying that many students accept an offer today rather than waiting for an offer that is substantially closer. Another way to assess the magnitude is to compare it to the size of heterogeneity in major and type preferences. For a large number of students, differences in utility between majors or types are not large enough to overcome the cost of waiting. This could lead to excessive acceptance in early rounds. Given the importance of a good match, this raises concerns about the time needed to run the sequential matching mechanism.

Figure 4: Waiting costs and major preferences



These concerns also differ for different groups of students. The estimates in Table 8 showed that the high school program and grade are important determinants of waiting costs. They are strongly determined by socio-economic background, leading to large differences in waiting costs (see Figure 6).

6.4 The benefit of a multi-round mechanism

Multi-round mechanisms have the flexibility to allow for seats to open up after students decide to drop out. However, they can also affect the final match through the frictions it imposes. Substantial

Figure 5: Waiting costs and program type preferences

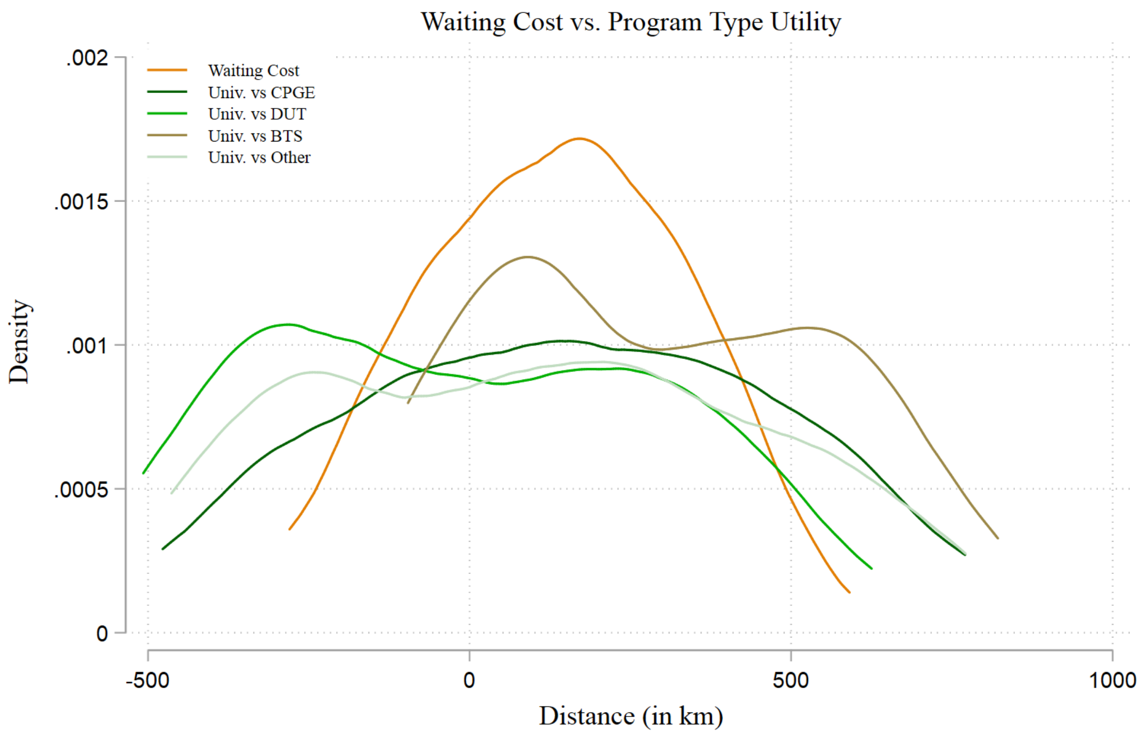
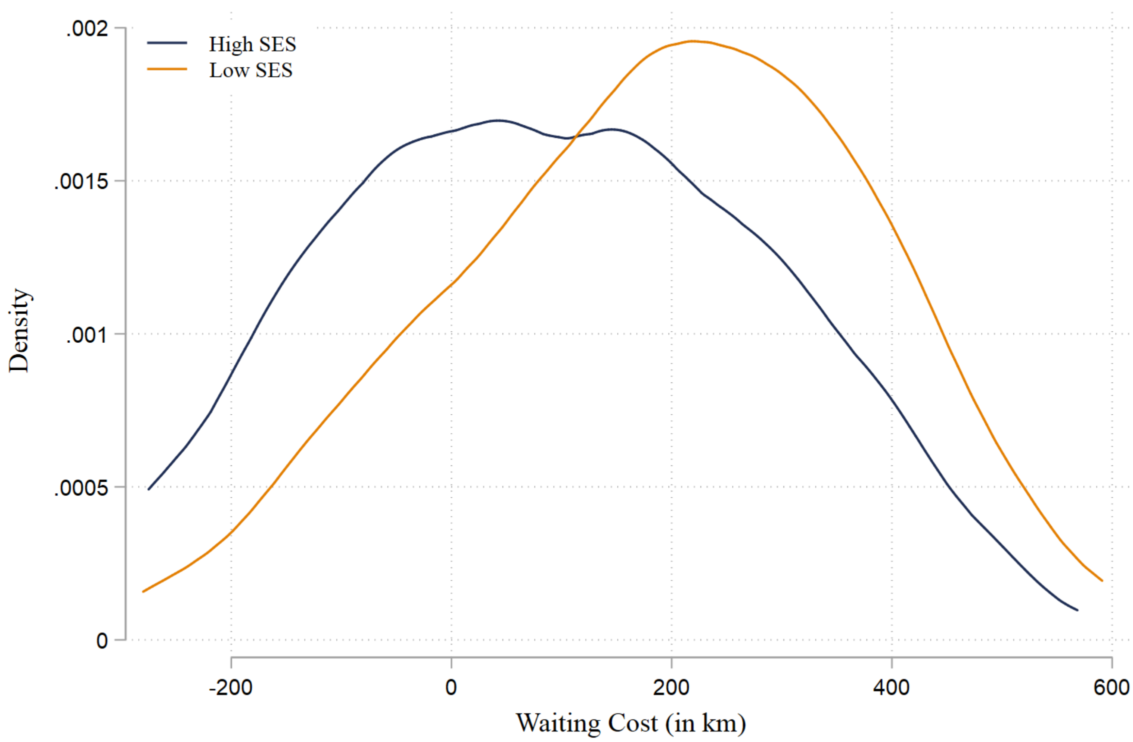


Figure 6: Waiting costs by SES



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.[12] We find that students gain substantially from the multi-round system. On average, the system provides a gain equivalent to enrolling 308 kilometers closer to home. While it increases welfare inequality, the different social groups gain. High SES students gain the equivalent of 343 kilometers, while low SES students gain 268 kilometers.

7 Concluding Remarks

In this paper we investigate the impact of running a multi-round college matching mechanism using rich administrative data from the French APB matching system. We find that a multi-round system has 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.

[12] In particular, we compute the utility for a student to accept immediately an offer, delay, or drop out. In the counterfactual scenario, we remove the option of delaying their decision. Students thus choose their preferred option between accepting their current offer or dropping out. Students with no offer in the first round get the utility from dropping out from the platform. We take into account the early acceptance advantage.

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A Appendix

A.1 Data overview

Tables A.1 and A.2 provide some details about the characteristics of students at different steps of the application procedure: from registering on the platform (Panel A) to accepting an offer (Panel D). We observe that 72% of the students of the initial sample submit a ROL (Panel A). Among them, 79% receive an offer during the main procedure (Panel B). 76% of the latter accept an offer on the platform (Panel C).

As we restrict the sample from students who registered on the platform to those accepting an offer, we observe that the share of students from the general high-school track increases: they represent 48% of the students who register to the platform (Panel A), but 60% of the students actually submitting a ROL (Panel B). This share further increases to 66% when restricting the sample to applicants receiving an offer during the main procedure (Panel C). The share of students from the professional high-school track follows the reverse path.

As expected, the share of students with a high grade[13] at the centralized exam increases when restricting the sample. For example, the share of students obtaining a "good" grade ("very good") increases by 4 points (3 points) when restricting the sample from students registered on the platform to those receiving an offer. This contrasts with the decrease in the share of students who failed the centralized exam, who represent 45% of those registered on the platform, but 40% of the applicants receiving an offer in the main procedure.

Finally, we observe an over-representation of students from the high SES group when we restrict the sample to applicants receiving offers during the main procedure (32%) compared to their share in the sample of students registering to the platform (27%). This pattern differs largely for students in the low SES group, who represent 28% of the students registering to the platform, but only 23% of those receiving an offer. Of course, this could simply reflect a positive correlation between SES status and the academic ability of a student.

[13]Grade at the centralized exam is classified in four broad categories: "very good" for a grade above 16, "good" for a grade between 14 and 16, "sufficiently good" for a grade between 12 and 14 and "sufficient" for a grade between 10 and 12. A grade below 10 means that the student failed the exam.

Table A.1: Panel A presents summary statistics for the full sample. Panel B presents summary statistics for the sample of students who submitted a valid ROL.

	Panel A: Full Sample		
	Mean	Standard Deviation	Total # Observations
Female	0.52	0.5	4,215,774
General HS Track	0.48	0.5	4,215,774
Technological HS Track	0.17	0.38	4,215,774
Professional HS Track	0.17	0.38	4,215,774
Other HS Track	0.17	0.38	4,215,774
BAC - $10 \leq$ Grade < 12	0.45	0.5	3,891,674
BAC - $12 \leq$ Grade < 14	0.27	0.44	3,891,674
BAC - $14 \leq$ Grade < 16	0.13	0.34	3,891,674
BAC - $16 \leq$ Grade	0.06	0.24	3,891,674
BAC - Retake	0.01	0.03	3,891,674
BAC - Fail	0.08	0.27	3,891,674
SES Status - High	0.27	0.45	3,951,227
SES Status - Medium High	0.14	0.35	3,951,227
SES Status - Medium Low	0.3	0.46	3,951,227
SES Status - Low	0.28	0.45	3,951,227
2014	0.24	0.43	4,215,774
2015	0.25	0.43	4,215,774
2016	0.25	0.43	4,215,774
2017	0.26	0.44	4,215,774
Students with Valid ROL	0.72	0.20	4,215,774
Total # Students			4,215,774

	Panel B: Students with Valid ROL		
	Mean	Standard Deviation	Total # Observations
Female	0.53	0.50	3,022,467
General HS Track	0.60	0.49	3,022,467
Technological HS Track	0.20	0.40	3,022,467
Professional HS Track	0.16	0.37	3,022,467
Other HS Track	0.03	0.18	3,022,467
BAC - $10 \leq$ Grade < 12	0.43	0.49	2,940,946
BAC - $12 \leq$ Grade < 14	0.28	0.45	2,940,946
BAC - $14 \leq$ Grade < 16	0.15	0.36	2,940,946
BAC - $16 \leq$ Grade	0.08	0.26	2,940,946
BAC - Retake	0.01	0.02	2,940,946
BAC - Fail	0.06	0.24	2,940,946
SES Status - High	0.30	0.46	2,940,946
SES Status - Medium High	0.15	0.36	2,940,946
SES Status - Medium Low	0.30	0.46	2,940,946
SES Status - Low	0.25	0.44	2,940,946
2014	0.24	0.42	3,022,467
2015	0.25	0.43	3,022,467
2016	0.25	0.43	3,022,467
2017	0.26	0.44	3,022,467
Students Receiving an Offer (PP)	0.79	0.40	3,022,467
Total # Students			3,022,467

Table A.2: Panel C presents summary statistics for the sample of students receiving an offer during the 'Procédure Principale'. Panel D presents summary statistics for the sample of students accepting an offer.

	Panel C: Students Receiving an Offer during the Procédure Principale		
	Mean	Standard Deviation	Total # Observations
Female	0.54	0.5	2,403,963
General HS Track	0.66	0.47	2,403,963
Technological HS Track	0.20	0.40	2,403,963
Professional HS Track	0.11	0.32	2,403,963
Other HS Track	0.02	0.15	2,403,963
Exam - $10 \leq$ Grade < 12	0.40	0.49	2,350,896
Exam - $12 \leq$ Grade < 14	0.29	0.45	2,350,896
Exam - $14 \leq$ Grade < 16	0.17	0.37	2,350,896
Exam - $16 \leq$ Grade	0.09	0.28	2,350,896
Exam - Retake	0.00	0.03	2,350,896
Exam - Fail	0.05	0.21	2,350,896
SES Status - High	0.32	0.47	2,360,898
SES Status - Medium High	0.15	0.36	2,360,898
SES Status - Medium Low	0.29	0.45	2,360,898
SES Status - Low	0.23	0.42	2,360,898
2014	0.18	0.43	2,403,963
2015	0.25	0.43	2,403,963
2016	0.27	0.43	2,403,963
2017	0.30	0.44	2,403,963
Students Accepting Offer (PP)	0.76	0.42	2,403,963
Total # Students			2,403,963

	Panel D: Students Answering 'Accept' in PP		
	Mean	Standard Deviation	Total # Observations
Female	0.53	0.50	1,839,901
General HS Track	0.67	0.47	1,839,901
Technological HS Track	0.20	0.40	1,839,901
Professional HS Track	0.11	0.31	1,839,901
Other HS Track	0.02	0.14	1,839,901
Exam - $10 \leq$ Grade < 12	0.41	0.49	1,801,246
Exam - $12 \leq$ Grade < 14	0.31	0.46	1,801,246
Exam - $14 \leq$ Grade < 16	0.18	0.38	1,801,246
Exam - $16 \leq$ Grade	0.10	0.30	1,801,246
Exam - Retake	0.00	0.02	1,801,246
Exam - Fail	0.00	0.06	1,801,246
SES Status - High	0.32	0.47	1,809,918
SES Status - Medium High	0.15	0.36	1,809,918
SES Status - Medium Low	0.29	0.45	1,809,918
SES Status - Low	0.23	0.42	1,809,918
2014	0.24	0.42	1,839,901
2015	0.25	0.43	1,839,901
2016	0.26	0.44	1,839,901
2017	0.25	0.43	1,839,901
Total # Students			1,839,901