College Admission Mechanisms and the Opportunity Cost of Time*

Olivier De Groote† Anaïs Fabre‡ Margaux Luflade§ Arnaud Maurel¶

January 17, 2024

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 and acceptance 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 and incomplete. We thank Joe Altonji, Zach Bleemer, Pierre Dubois, Nezih Guner, Juanna Joensen, Thierry Magnac, Bob Miller, Min Park, Chris Taber and seminar participants at Tilburg University, Toulouse School of Economics, University of Bristol, and the Workshop in Honor of Pierre-Andre Chiappori, the 2024 AEA Meetings, 2023 BSE Summer Workshop on Structural Microeconometrics, 2023 SOLE meetings, the 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.

†Toulouse School of Economics, University of Toulouse Capitole, olivier.de-groote@tse-fr.eu.

‡Toulouse School of Economics, University of Toulouse Capitole, anais.fabre@tse-fr.eu.

§University of Pennsylvania, mluflade@sas.upenn.edu.

¶Duke University, NBER and IZA, apm16@duke.edu.

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., 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 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 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, 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 299 kilometers closer to home. However, the gains are not equally distributed. The two highest SES groups gain the equivalent of 299 to 333 kilometers, while the two lowest experience a somewhat smaller gain, equivalent to 259 to 275 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). 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 plat-

[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.

form and off-platform options. As such, our analysis complements recent work by Kapor et al. (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.[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

[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.

[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.

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. 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. Our empirical analysis focuses on students in the *general* track, who can choose one of three high-school majors: sciences, humanities, and 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 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 participate, in a given year, both 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 the her ROL.[4][5] The matching algorithm is then run again by the clearinghouse, excluding students who dropped out and using the same ROLs and priorities as in the first round, to assign the remaining vacancies to unmatched students and to those who chose to delay their decision. After receiving their second-round offer, students may again *accept*, *drop out*, or *delay*. In the third and final round, the clearinghouse produces a final set of offers, which students can only accept (or refuse

[4] 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.

[5] 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 small number of students used this option we exclude it from the analysis.

Table 1: Types of post-secondary programs in France

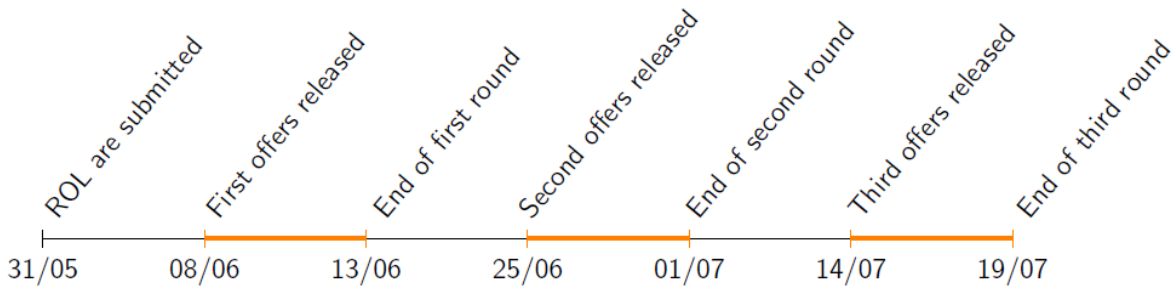
On-platform programs excluding high-school performance from their admission criteria	
Bachelor programs	Three-year programs offered by public universities Graduates can enter the labor force or further pursue a Master's degree Deliver the degree of *Bachelor*
On-platform programs including high-school 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)

and drop out). Figure 1 illustrates the timing of the process in 2015.

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*

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.

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 (specifically, whether or not the student lives in the region the program is located in[6]) 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 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.[7] As a matter

[6]See Figure A-1 for the map of the regions used for the construction of priorities (*académies*).

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

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 show demographics, residential ZIP code, a high-school identifier, the track and major chosen in high school, performance at the national end-of-high-school exam, as well as the exact 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.

Student sample. We focus our attention to the 2015 assignment procedure and further restrict the sample to students graduating from the *general* high-school track and participating in the college assignment procedure for the first time in 2015.[8] Descriptive statistics are shown in Table 2. Students submit on average slightly more than seven choices in their ROL. Of importance to motivate our research question, students' final assignment is on average ranked higher in their ROL than the first offer they receive (rank 1.95 vs. 2.19).

On the decision to *delay* acceptance. In this paragraph, we document the use by students of their option to delay in the 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.

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

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

Table 2: Sample description

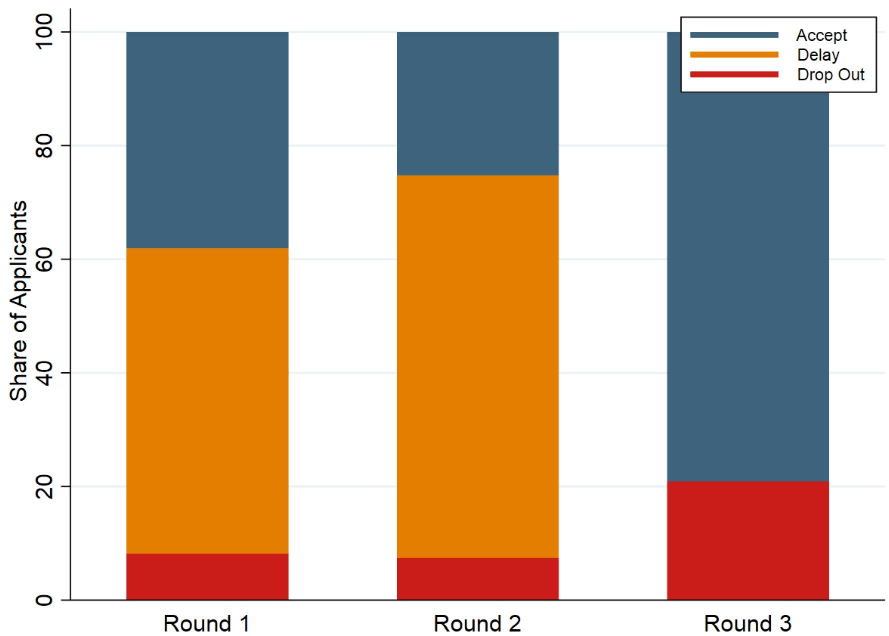
Demographics	
Female	0.57
High SES	0.40
Medium-high SES	0.16
Medium-low SES	0.27
Low SES	0.17
Means-based scholarship recipient	0.13
High-school major	
Sciences major	0.54
Social Sciences major	0.31
Humanities major	0.15
End-of-high-school-exam performance	
Highest honors ($> 16/20$)	0.12
High honors (14 to 16/20)	0.19
Honors (12-14/20)	0.28
Pass (10-12/20)	0.40
Applications and offers	
Average number of programs listed	7.09
Average rank of Round-1 offer	2.19
Average rank of accepted offer	1.95
Final match characteristics	
Bachelor program	0.52
Prep-school program	0.12
Technical program	0.10
Vocational program	0.05
STEM major	0.33
Econ./Law major	0.16
Humanities major	0.20
Other major	0.17
Urban location (Main city)	0.47
Avg. monthly rent (cond. on urban location, EUR)	448
Observations[1]	67,425

This table shows descriptive statistics on the student sample and their final assignment. Unless otherwise specified, numbers provided are sample shares. See Appendix A for details about the definition of SES categories, end-of-high-school-exam performance, and the construction of average rent.

[1] Statistics are shown for random 25% sample of the population of interest (2015 graduates from the general high-school track participating in the college assignment procedure for the first time in 2015). This random sample is used for the structural estimation.

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 20% accept their assignment. In the third round, when students cannot choose delay, 80% 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.

Table 3 illustrates the expected benefits of choosing the delay option. Twenty percent of the students choosing to delay in Round 1 receive a new (high-ranked) offer in Round 2, and 25% of the students delaying in Rounds 1 and 2 receive a better offer in Round 3.

Table 3: Share of students receiving new offers after choosing *delay*

	Share
Receiving better offer in Round 2, cond. on choosing *delay* in Round 1	0.20
Receiving better offer in Round 3, cond. on choosing *delay* in Rounds 1 and 2	0.25

This table reports the share of student receiving a new (higher-ranked) offer conditional on choosing delay in the previous rounds.

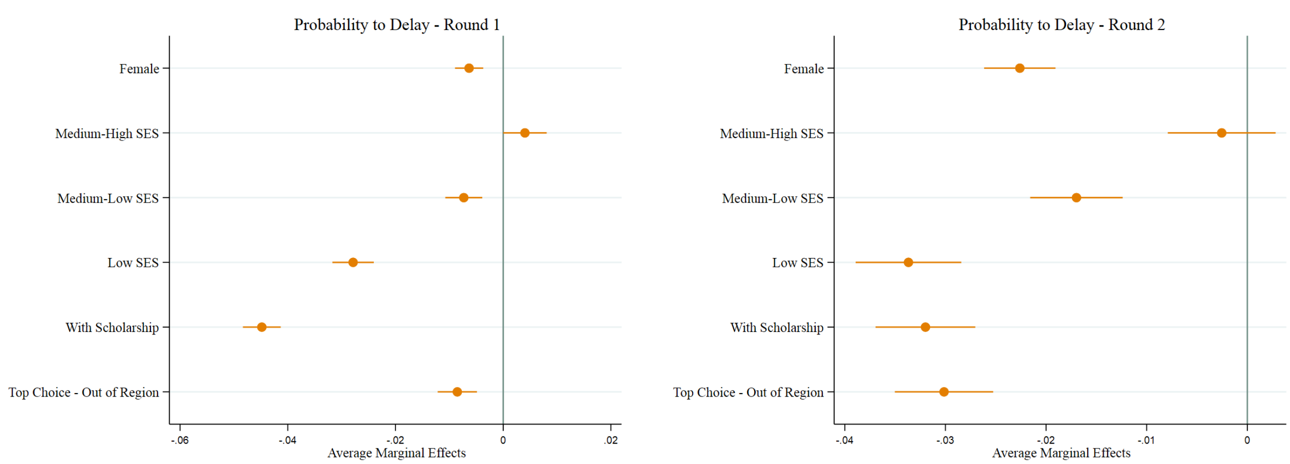
Table 4 and Figure 3 illustrate the heterogeneity in the choice of the delay option across demographics. Table 4 reports the share of students choosing the delay option in each round (among those who did not receive an offer from their top-ranked choice) broken down by SES. The table shows the existence of a gradient across SES in the use of the delay option. In particular, high-SES participants are eight (six) percentage points more likely to choose *delay* than low-SES participants in Round 1 (Round 2). To further explore this heterogeneity, we estimate a logit regression and report in Figure 3 the average marginal effects of several student characteristics on the probability to use *delay* in each round. While female students are less likely to choose to delay, indicators of lower income (namely, low SES and eligibility for means-based scholarship) remain the best predictors of the choice to delay. Applicants whose top choice is outside of their home region are also less likely to delay, consistent with housing costs being more salient in these cases.

Table 4: Share of eligible students choosing to *delay*, by SES

	Round 1	Round 2
High SES	0.57	0.67
Medium-high SES	0.56	0.66
Medium-low SES	0.54	0.64
Low SES	0.49	0.61

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), broken down by SES.

Figure 3: Average marginal effects of demographics on the decision to *delay*, by round



This figure shows the average marginal effects of demographics on the decision to *delay* estimated, for each round separately, using a logit regression.

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 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:

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

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 $\mathcal{J}$.

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 $j_t = 0$, 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. This could also reflect psychic costs, which are high if the student is impatient, low (and even negative) if they procrastinate (Akerlof, 1991). 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:

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

where γ denotes Euler's constant. 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 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. 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:

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

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 Bachelor programs in rank 1 also usually put a Bachelor program in rank 2, it indicates the existence of an unobserved type that prefers Bachelor 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.[9] λ_τ is a $K \times 1$ vector of parameters capturing the impact of an unobserved student type.

A first set of program characteristics consists in indicator variables for each program type and major. Since only differences in utility are identified, we estimate the difference with a Bachelor program, in a STEM major, by including indicator variables for the other types (prep-school programs, technical programs, vocational programs, and others) and majors (Econ/Law, Humanities, Services, and Production[10]). 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.[11] We also include proxies for local housing costs by distinguishing between programs in and outside cities. For programs in cities, we further distinguish by measures of local rents. Finally, as some prep-school programs offer dorms, for this type of programs, we include indicators for whether dorms are 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 parametrized 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

[9] 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.

[10] The service and production majors are common among technical and vocational programs.

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

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:

$$\omega_t(S_i, \tau) = \psi_s S_i + \beta_\tau + \gamma_t \tag{11}$$

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

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 relationship 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.[12] 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.

[12]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.

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:

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

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 a rank-ordered logit model on the ROLs.[13] 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.

5.3.1 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

[13]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.

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

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

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

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

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

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.[14]

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 therefore follow the estimation approach of Arcidiacono & Miller (2011). This is an adaptation of

[14] 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.

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.

6 Estimation Results and Counterfactual Simulations

In this section we report all utility estimates.[15] 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 5, Table 6 and Table 7. 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: 0.125 (with standard error of 0.005). This estimate implies that the standard deviation of the "trembling hand" error in the ROL is quite small as it amounts to about 12% 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* serve as benchmark categories for programs type and field of study. To interpret the role of individual characteristics, the benchmark is a male, high-SES, not eligible to a scholarship, who graduated high-school with a sciences major and highest honors, and with unobservable type 1.

The first part of Table 5 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 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, prep-school programs are, on average, valued less than Bachelor programs by the benchmark group, equivalent to an increase in distance of 107 km ($= 100 \times (0.954/0.888) = 107$).

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

Table 5: Program utility (part 1 of 3)

Common component		
Program type (benchmark = Bachelor prog.)		
Prep-sch. prog.	-0.954	(0.057)
Technical prog.	1.717	(0.168)
Vocational prog.	-1.981	(0.203)
Other prog.	1.090	(0.054)
Program major (benchmark = STEM)		
Econ./Law	-1.014	(0.044)
Humanities	-3.419	(0.054)
Production	-2.942	(0.183)
Services	-4.279	(0.144)
Same catchment area	1.281	(0.014)
Same region	0.783	(0.013)
Main City	-0.489	(0.022)
Main City × Rent	0.205	(0.004)
Dorm Available	0.260	(0.031)
Dorm Available × Applied to Dorm	-0.397	(0.021)
Distance	-0.888	(0.007)
Heterogeneity		
SES Group (benchmark = High SES)		
Medium-High × Prep-sch. prog.	-0.260	(0.042)
Medium-High × Technical prog.	-0.233	(0.094)
Medium-High × Vocational prog.	0.044	(0.097)
Medium-High × Other prog.	-0.341	(0.048)
Medium-Low × Prep-sch. prog.	-0.418	(0.039)
Medium-Low × Technical prog.	-0.768	(0.083)
Medium-Low × Vocational prog.	-0.338	(0.085)
Medium-Low × Other prog.	-0.635	(0.046)
Low × Prep-sch. prog.	-0.668	(0.049)
Low × Technical prog.	-1.083	(0.101)
Low × Vocational prog.	-0.496	(0.101)
Low × Other prog.	-0.891	(0.059)
Medium-High × Econ./Law	-0.375	(0.042)
Medium-High × Humanities	0.036	(0.043)
Medium-High × Production	0.302	(0.102)
Medium-High × Services	0.185	(0.088)
Medium-Low × Econ./Law	-0.272	(0.037)
Medium-Low × Humanities	-0.032	(0.038)
Medium-Low × Production	0.958	(0.090)
Medium-Low × Services	0.692	(0.077)
Low × Econ./Law	-0.469	(0.045)
Low × Humanities	-0.258	(0.047)
Low × Production	1.045	(0.108)
Low × Services	0.689	(0.094)

Standard errors in parentheses.

Table 6: Program utility (part 2 of 3)

Heterogeneity (continued)		
Grade (benchmark = Highest honors)		
High honors × Prep-sch. prog.	-2.402	(0.054)
High honors × Technical prog.	-0.192	(0.182)
High honors × Vocational prog.	0.085	(0.216)
High honors × Other	-0.728	(0.056)
Honors × Prep-sch. prog.	-4.091	(0.057)
Honors × Technical prog.	-0.721	(0.175)
Honors × Vocational prog.	-0.272	(0.207)
Honors × Other prog.	-1.495	(0.060)
Pass × Prep-sch. prog.	-5.487	(0.061)
Pass × Technical prog.	-1.849	(0.173)
Pass × Vocational prog.	-0.637	(0.204)
Pass × Other prog.	-2.257	(0.063)
High honors × Econ./Law	0.187	(0.045)
High honors × Humanities	-0.380	(0.048)
High honors × Production	1.170	(0.201)
High honors × Services	1.709	(0.159)
Honors × Econ./Law	0.202	(0.045)
Honors × Humanities	-0.857	(0.048)
Honors × Production	3.250	(0.192)
Honors × Services	3.776	(0.153)
Pass × Econ./Law	0.030	(0.045)
Pass × Humanities	-0.936	(0.048)
Pass × Production	4.446	(0.189)
Pass × Services	5.020	(0.151)
High School Program (benchmark = Sciences)		
Social Sciences × Prep-sch. prog.	-0.941	(0.036)
Social Sciences × Technical prog.	0.189	(0.079)
Social Sciences × Vocational prog.	-0.013	(0.080)
Social Sciences × Other	-0.981	(0.055)
Humanities × Prep-sch. prog.	-0.107	(0.051)
Humanities × Technical prog.	0.226	(0.140)
Humanities × Vocational prog.	0.878	(0.134)
Humanities × Other prog.	-0.482	(0.059)
Social Sciences × Econ./Law	3.693	(0.039)
Social Sciences × Humanities	3.101	(0.041)
Social Sciences × Production	-0.021	(0.102)
Social Sciences × Services	3.809	(0.079)
Humanities × Econ./Law	3.582	(0.077)
Humanities × Humanities	5.535	(0.075)
Humanities × Production	-1.771	(0.246)
Humanities × Services	1.833	(0.147)

Standard errors in parentheses.

Table 7: Program utility (part 3 of 3)

Heterogeneity (continued)		
Scholarship Status (benchmark = Without Scholarship)		
Scholarship recipient × Prep-sch. prog.	0.188	(0.050)
Scholarship recipient × Technical prog.	0.033	(0.104)
Scholarship recipient × Vocational prog.	0.011	(0.103)
Scholarship recipient × Other prog.	0.026	(0.061)
Scholarship recipient × Econ./Law	0.072	(0.046)
Scholarship recipient × Humanities	-0.074	(0.048)
Scholarship recipient × Production	-0.245	(0.111)
Scholarship recipient × Services	-0.329	(0.098)
Sex (benchmark = Male)		
Female × Prep-sch. prog.	-0.419	(0.030)
Female × Technical prog.	-1.219	(0.066)
Female × Vocational prog.	-0.848	(0.067)
Female × Other prog.	-0.759	(0.035)
Female × Econ./Law	0.402	(0.029)
Female × Humanities	0.902	(0.030)
Female × Production	0.204	(0.072)
Female × Services	1.248	(0.061)
Unobserved Type (benchmark = Type 1)		
Type 2 × Prep-sch. prog.	4.994	(0.063)
Type 2 × Technical prog.	0.861	(0.078)
Type 2 × Vocational prog.	0.474	(0.081)
Type 2 × Other prog.	1.669	(0.045)
Type 2 × Econ./Law	-0.294	(0.032)
Type 2 × Humanities	1.786	(0.041)
Type 2 × Production	-3.558	(0.085)
Type 2 × Services	-4.217	(0.073)

Standard errors in parentheses.

To capture differences in local amenities 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 find that at 0 rent, students prefer not to live in a city, but they prefer locations with better amenities.

The rest of Table 5, as well as Tables 6 and 7 describe the heterogeneity in program preferences, i.e. how utilities differ for the students that outside of the benchmark group. The main findings the following. As compared to the benchmark group, lower SES students and students with lower end-of-high-school performance are more likely to consider Vocational programs as an alternative to Bachelor programs, and less likely to consider Technical and Prep-school programs. All other things equal, female students have a relatively lower preference from STEM field that any for other field. All other things equal, students graduating with a humanities or social sciences high-school major have a relatively stronger preference for studying humanities, econ./law, or services in college as compared to STEM.

Table 7 concludes with the heterogeneity that is not explained by observable characteristics. Forty-seven percent of the sample is estimated to be of unobserved type 2. This type is capturing a much higher 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 562 km closer to home, all other things constant. This type is also much more likely to consider a program in Humanities or Econ./Law. 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 (Φ and ϕ_τ). Estimates are shown in Table 8.

Because of housing considerations, accepting a program early in the process can have substantial benefits for students. Table 8 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 0.125 utils. To interpret this number, note that this is about equivalent to the disutility to travel 100 km for a program,

Table 8: Utility from Early Acceptance

Distance		
Distance	0.125	(0.022)
Distance × Female	0.013	(0.016)
Distance × Type 2	-0.027	(0.016)
Distance × Medium-High SES	-0.042	(0.022)
Distance × Medium-Low SES	-0.012	(0.019)
Distance × Low SES	-0.054	(0.026)
Distance × Scholarship recipient	-0.032	(0.025)
Distance × High honors	0.014	(0.022)
Distance × Honors	0.006	(0.022)
Distance × Pass	0.050	(0.022)
Distance × Social Sciences	-0.042	(0.018)
Distance × Humanities	-0.026	(0.022)
Main City		
Main City	0.125	(0.022)
Main City × Female	-0.083	(0.087)
Main City × Type 2	0.000	(0.087)
Main City × Medium-High SES	0.072	(0.129)
Main City × Medium-Low SES	-0.025	(0.109)
Main City × Low SES	-0.145	(0.134)
Main City × Scholarship recipient	0.054	(0.138)
Main City × High honors	-0.071	(0.148)
Main City × Honors	-0.325	(0.141)
Main City × Pass	-0.378	(0.136)
Main City × Social sciences	0.136	(0.095)
Main City × Humanities	-0.191	(0.124)
Main City × Rent		
Main City × Rent	-0.037	(0.026)
Main City × Rent × Female	0.027	(0.017)
Main City × Rent × Type 2	0.005	(0.017)
Main City × Rent × Medium-High SES	-0.002	(0.026)
Main City × Rent × Medium-Low SES	-0.002	(0.021)
Main City × Rent × Low SES	0.016	(0.027)
Main City × Rent × Scholarship recipient	0.014	(0.027)
Main City × Rent × High honors	0.000	(0.027)
Main City × Rent × Honors	0.048	(0.026)
Main City × Rent × Pass	0.040	(0.025)
Main City × Rent × Social sciences	-0.034	(0.019)
Main City × Rent × Humanities	0.030	(0.023)

Standard errors in parentheses.

which is estimated to be -0.111 ($= -0.888 \times 0.125$). This suggests that early knowledge on where to enroll can entirely 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). As student demographic and academic background might affect the set of available (affordable) 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). While the effects for rents are small and insignificant, students are more likely to accept early a program located in a city.

6.3 Waiting costs and drop out utility

Estimates for the waiting costs (ψ) and drop out utility (α) are shown in Table 9. Note that the tables report the negative of the waiting costs parameters (-ψ) so they should be interpreted as utility, rather than disutility.

While students on average experience a cost from using the drop out option, high SES, being female, and graduating high school with the humanities or social sciences major and a lower performance are individual characteristics associated with a relatively lower cost from dropping out. On the contrary, type-1 students on average derive a positively value from using the delay option (potentially capturing procrastination), while this value is much lower for type-2 students. The value of the delay option is also notably higher for highest-honors students.

To better interpret the magnitude of waiting costs, it is useful to compare waiting costs to the valuation of different program characteristics. To do this comparison, we convert waiting costs to express them in distance-equivalent terms (in kilometers, $= \psi/(0.00888 \times 0.125)$). 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 benchmark) in distance-equivalent terms. Figure 4 shows the predicted distribution of waiting costs (in distance-equivalent terms) in comparison to the relative valuation of programs types (top panel) and fields of study (bottom panel). Focusing first on the distribution of waiting costs themselves, we find that waiting costs are positive (i.e. waiting utility is negative) for a majority of students. The median waiting cost corresponds to 141 kilometers, implying that many students would accept an offer today rather than waiting for an offer that is not substantially closer. Turning to the comparison of waiting

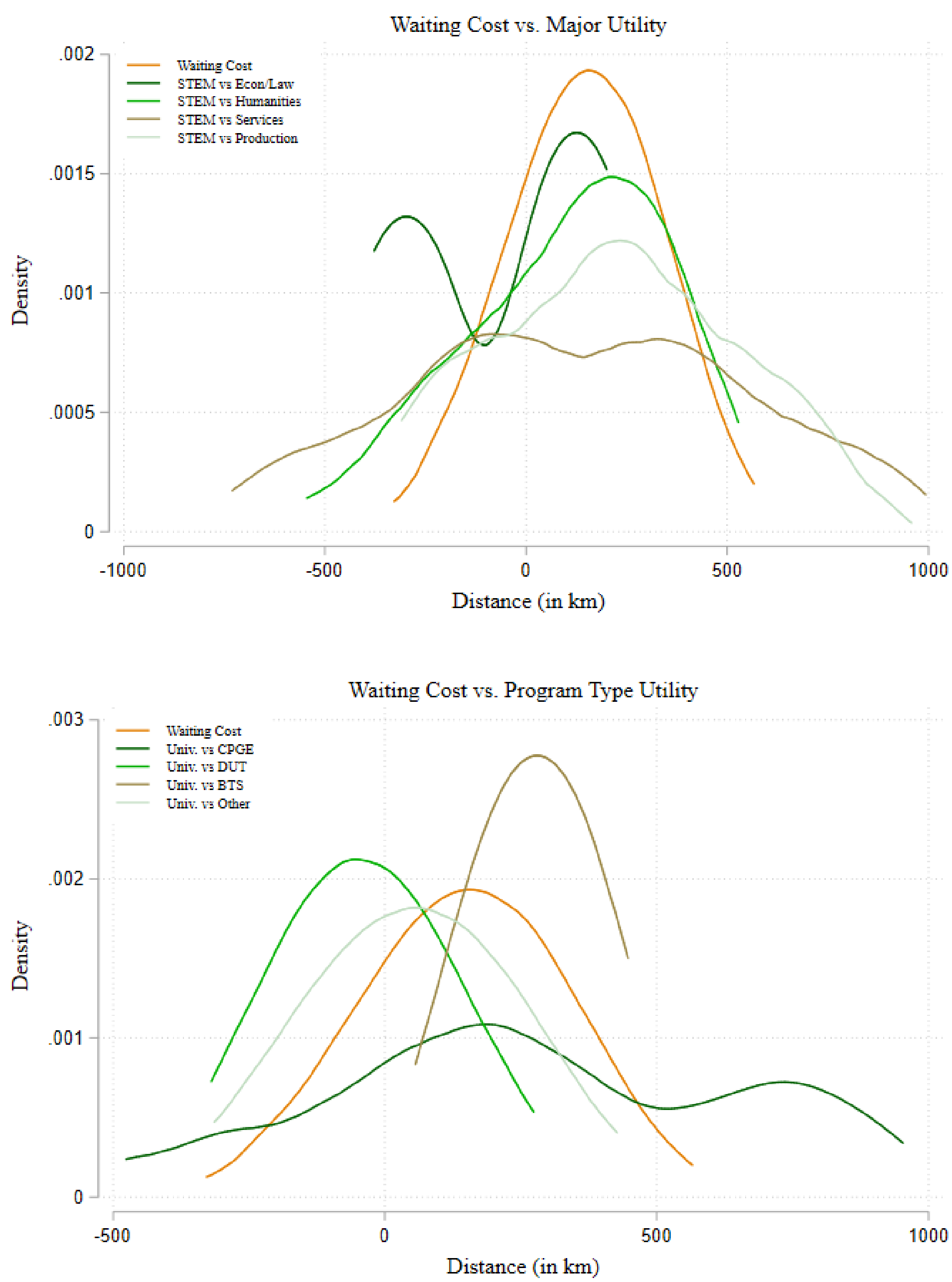
Table 9: Utility from Waiting & Drop Out

Common component		
Delay	0.190	(0.064)
Drop Out × Round 1	-2.546	(0.061)
Drop Out × Round 2	-2.229	(0.063)
Drop Out × Round 3	-1.709	(0.061)
Heterogeneity		
SES (benchmark = High SES)		
Medium-High × Delay	0.013	(0.048)
Medium-Low × Delay	-0.021	(0.041)
Low × Delay	0.026	(0.051)
Medium-High × Drop out	-0.312	(0.046)
Medium-Low × Drop out	-0.285	(0.039)
Low × Drop out	-0.548	(0.049)
Scholarship Status (benchmark = Without Scholarship)		
Scholarship recipient × Delay	-0.048	(0.054)
Scholarship recipient × Drop out	-0.325	(0.052)
Sex (benchmark = Male)		
Female × Delay	0.047	(0.034)
Female × Drop out	0.294	(0.033)
End-of-high-school-exam performance (benchmark = Highest honors)		
High honors × Delay	-0.153	(0.064)
Honors × Delay	-0.267	(0.060)
Pass × Delay	-0.462	(0.058)
High honors × Drop out	-0.081	(0.063)
Honors × Drop out	0.158	(0.059)
Pass × Drop out	0.397	(0.057)
Unobserved Heterogeneity (benchmark = Type 1)		
Type 2 × Delay	-0.158	(0.033)
Type 2 × Drop out	0.026	(0.031)
High-school Major (benchmark = Sciences)		
Social Sciences × Delay	0.102	(0.036)
Humanities × Delay	-0.130	(0.050)
Social Sciences × Drop out	0.775	(0.037)
Humanities × Drop out	0.768	(0.051)

Standard errors in parentheses.

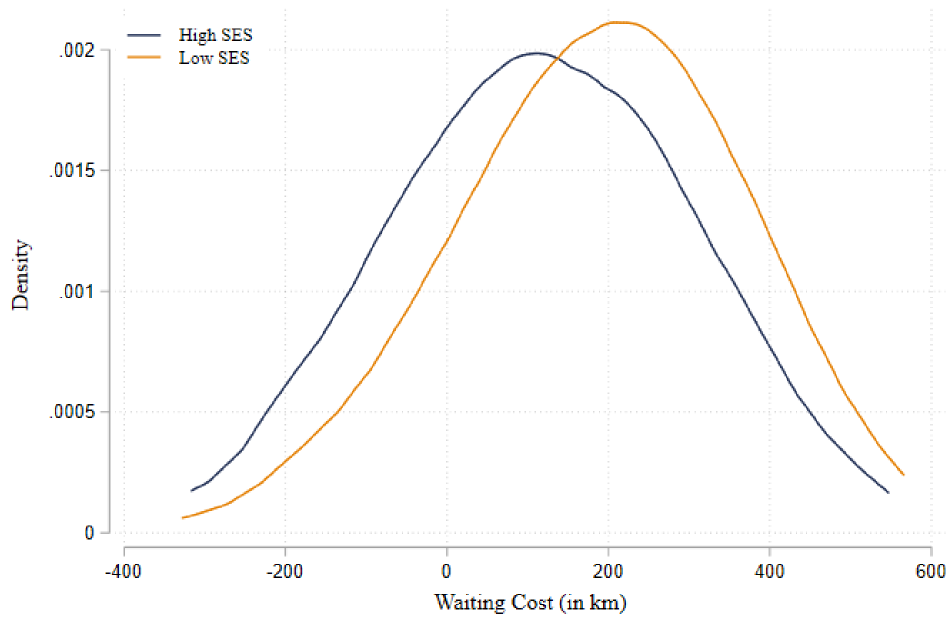
costs with the relative valuation of program characteristics, we find that, overall, the magnitude of waiting costs offset the utility gains from being assigned to a program in more preferred type or field of study. In other words, for many students, differences in utility between majors or types are not large enough to overcome the cost of delaying acceptance.

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



Finally, Figure 5 further illustrates the heterogeneity in estimated waiting costs by showing their distribution for the highest and lowest SES groups separately. It shows that waiting costs tend to be higher for low SES students.

Figure 5: Waiting costs by SES



6.4 The benefit 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.[16]

[16]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.

Table 10: 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	299	0.21	691	0.50
By SES				
High	333	0.25	698	0.53
Medium-high	299	0.20	713	0.50
Medium-low	275	0.19	673	0.50
Low	259	0.16	677	0.46

[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 1,373 km (1,431 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: 1,345 km; 1,499 km; 1,428 km; 1,576 km (1,328 km; 1,435 km; 1,355 km; and 1,469 km, respectively).

In that scenario, after receiving their first-round assignment, students can 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 10. On average, the multi-round procedure provides a gain equivalent to enrolling 299 kilometers closer to home relative to the single-round procedure. To better interpret this magnitude, it is useful to know that, on average, gaining admission to the top-ranked program instead of the second-ranked program corresponds to a gain of 79 kilometers. Gains from multiple rounds are heterogeneous across SES groups. Higher-SES groups welfare gains equivalent to a reduction in distance from home of 299 to 333 kilometers, against 259–275 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. We find that the multi-round mechanism increases welfare by 56% more or highest SES group than for the lowest.

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.

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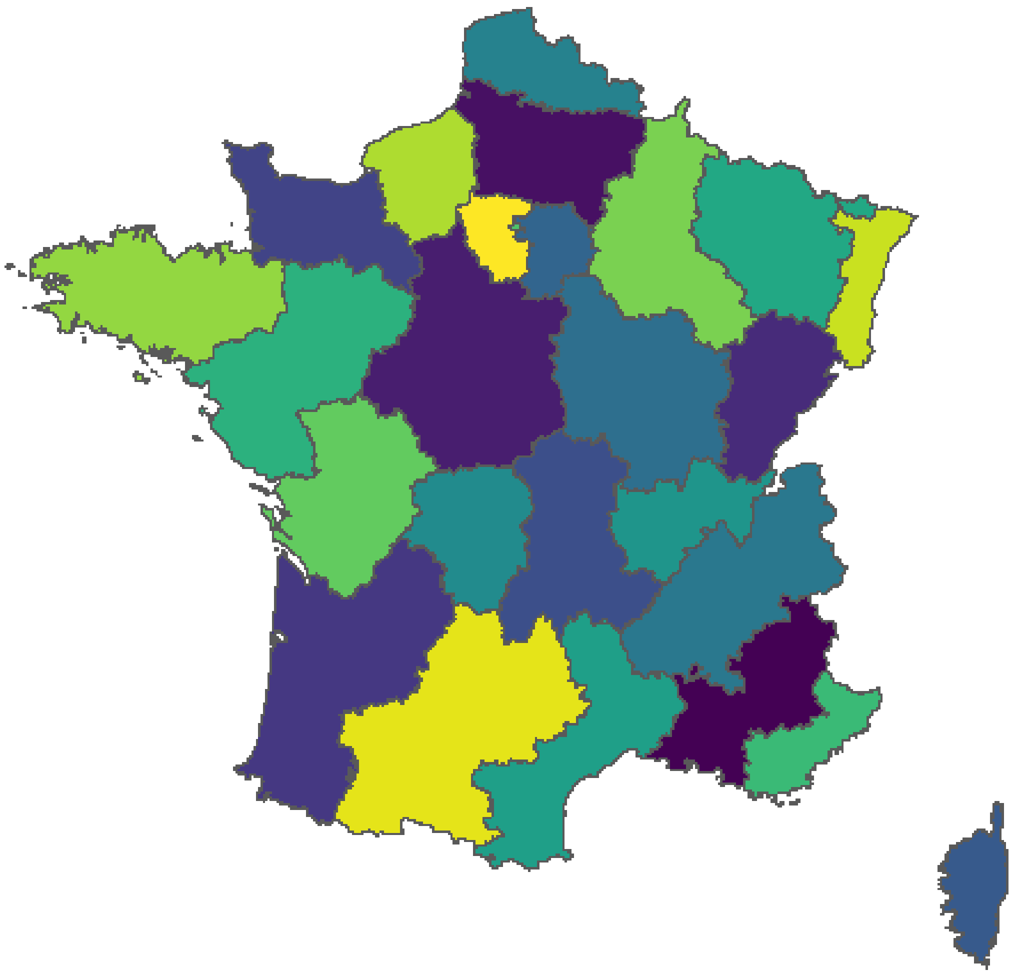
A Data appendix

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.