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Abstract

We document quasi-experimental evidence against the common assumption in the matching literature that agents have full information on their own preferences. In Germany's university admissions, the first stages of the Gale-Shapley algorithm are implemented in real time, allowing for multiple offers per student. We demonstrate that nonexploding early offers are accepted more often than later offers, despite not being more desirable. These results, together with survey evidence and a theoretical model, are consistent with students' costly discovery of preferences. A novel dynamic multioffer mechanism that batches early offers improves matching efficiency by informing students of offer availability before preference discovery.

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Introduction

Research on the design of matching markets has been a success story, not least because it has resulted in improved designs for school choice, university admissions, and entry-level labor markets (Roth and Peranson, 1999; Abdulkadiroğlu, Pathak and Roth, 2005b; Abdulkadiroğlu et al., 2005a). An important contributor to these successes has been market centralization, which aims at promoting efficiency—for instance, by reducing congestion and market unraveling (Roth, 1990).

Coupled with growing market centralization is the near-universal adoption of singleoffer mechanisms, especially the Deferred Acceptance (DA) mechanism (Gale and Shapley, 1962). Such mechanisms require every agent to rank her potential match partners before *at most one match offer* per agent is generated.[1] The widespread use of single-offer mechanisms is a direct consequence of the common assumption in the matching literature that every agent has full information on her own preferences (e.g., Roth and Sotomayor, 1990; Abdulkadiroğlu and Sönmez, 2003). Under this assumption, an agent can effortlessly rank match partners according to her preferences even though she is uncertain about eventual offers.

Yet full information on one's own preferences is unlikely to hold in practice. Take university admissions as an example. A student often has access to hundreds if not thousands of university programs.[2] Each program is a combination of a university and a major and has multi-dimensional characteristics including academic quality, courses offered, and quality of life. A student needs to invest time and effort to learn about program quality and discover her preferences. As a result, it could be welfare-improving to adopt mechanisms that allow students to hold multiple offers *before* they have to rank programs. In such a *dynamic multioffer* mechanism, early offers inform students of their admission chances and hence allow them to learn about programs more efficiently.

The first contribution of our study is to provide unambiguous empirical evidence against the assumption that students have full information on their own preferences. In

[1]When a single-offer mechanism is used in many-to-one matching, such as school choice and college admissions, a school that can accept multiple students will receive multiple match offers. However, a student can attend only one school and will obtain at most one offer.

[2]As more and more market segments are integrated into centralized markets with a single-offer mechanism, the number of potential match partners for a student can be huge. This trend is observed beyond university admissions. For instance, charter school and traditional public school admissions have been unified in a single-offer centralized design in Denver (Abdulkadiroğlu et al., 2017) and New Orleans (Abdulkadiroğlu et al., 2020).

an administrative data set on university admissions in Germany, we identify a quasi experiment in which the arrival time of admission offers is as good as random. We show that a student is more likely to accept an early offer relative to later offers, despite the fact that offers do not expire until the end of the admissions procedure. This early-offer effect cannot be reconciled with the assumption that students have full information on their own preferences but is instead consistent with students discovering them at a cost. This interpretation is further corroborated by direct evidence from a survey of students.

Our second contribution is to make a case for dynamic multioffer mechanisms in settings with nonnegligible costs of preference discovery. An example of such a mechanism is used in Germany's university admissions. A student who has received an early offer from a program is certain that this program is available to her and can thus target her learning more efficiently. However, the random arrival of offers may lead students to suboptimally accept early offers. We therefore propose a new multioffer mechanism that batches early offers. The benefits of the new mechanism are shown in a theoretical model and in simulations based on the data from Germany. In particular, the new mechanism dominates the DA, the most widely used single-offer mechanism.

Our empirical analysis exploits a procedure called *Dialogorientiertes Serviceverfahren* (DoSV; literally, dialogue-oriented service procedure) that is used for admissions to overdemanded university programs in Germany. Admission decisions are made by each program separately. The procedure is based on the program-proposing Gale-Shapley (GS) algorithm but differs from the standard implementation in that each student can defer her commitment to a rank-order list (ROL) of programs. Specifically, the DoSV implements the first stages of the GS algorithm in real time and allows students to hold multiple offers. During this phase of 34 days, all offers and acceptances are communicated via a clearinghouse, with students and programs interacting as if in a decentralized market. Programs make admission offers to their preferred students in real time, no offer expires until the end of the procedure, and students can decide to accept an offer and exit the procedure, to retain all offers, or to keep only a subset of their offers, also in real time.

At the end of the multioffer phase, students who have not yet accepted an offer are required to finalize their ROLs and enter a single-offer phase in which the computerized program-proposing GS algorithm is run for the remaining students and seats.[3] For a

[3]The sequential filling of seats is also a feature of a separate procedure that was used for admissions to medical programs in Germany (Braun, Dwenger and Kübler, 2010; Westkamp, 2013; Braun et al.,

student with offers from the multioffer phase, the highest-ranked offer in her final ROL is kept and will not be taken away from her unless she receives an offer from a program that is ranked higher in her final ROL. The single-offer phase ensures that a stable matching (with respect to stated preferences) is reached. Thus, unraveling does not play a role in this market.[4]

Our data set contains every event during the admission process for 2015–16 as well as its exact timing. We define a program as being *feasible* to a student if the student has applied to the program and would receive its admission offer as long as she does not exit the procedure early. There are $21,711$ students in our data set who have at least two feasible programs and have accepted one of them. We find that, relative to an offer arriving in the later, single-offer phase, an offer that arrives during the multioffer phase—which we define as an *early offer*—is more likely to be accepted.

The early-offer effect is sizable when we calculate its impact on offer acceptance. In our sample, the average probability of a feasible program being accepted is 0.385. An early offer that is not the first one raises the acceptance probability by 8.7 percentage points—a 27.9% increase. More significantly, the first early offer increases the acceptance probability by 11.8 percentage points—a 38.3% jump.[5]

We rule out a range of possible explanations of the early-offer effect through additional data analyses. The effect is unlikely to be driven by students' preferences for being ranked high by a program, an immediate reaction, pessimism about future offers, the need for a head start in house hunting, or dislike of being assigned by a computerized algorithm.

Our preferred explanation is that the early-offer effect is driven by students' costly discovery of their preferences over programs. From a student survey, we find direct evidence that at the start of the procedure, many students do not yet have clear preferences over programs. Furthermore, they tend to invest more time learning about the universities that made them an early offer, and early offers influence their perceptions of the programs.

These empirical findings can be formalized in a model of university admissions with

2014). There, quotas are filled one after the other, each quota with its own ROLs and matching algorithm (Boston Immediate Acceptance or GS). In contrast, the DoSV is based on one algorithm (GS) for all seats, but its early stages resemble a decentralized market.

[4]Decentralized markets without such a phase guaranteeing a stable outcome have been studied theoretically by Niederle and Yariv (2009) and experimentally by Echenique and Yariv (2013).

[5]Another way to gauge the magnitude of the effect is to use distance from a student's home to the university where the program is located as a numeraire. At the sample mean of 126 km, an early offer amounts to reducing the distance to the corresponding program by 61 km. The first early offer has an even larger effect, equivalent to a reduction of 79 km.

preference discovery and are illustrated in a numerical example. A student can learn her valuation of a university program only after paying a cost. She applies to two programs and has access to an outside option of a known value. In expectation, each program makes her an offer with some probability, which determines the student's endogenous learning decision. An early offer from a program, which leads the student to update the corresponding offer probability to one, increases her incentive to learn about this program. Finally, learning about a program increases the probability that its offer is accepted, leading to the early-offer effect.

These results provide novel insights for market design regarding the benefits of dynamic multioffer mechanisms. In a generalized model with preference discovery, we evaluate three mechanisms: (i) the DA, which requires students to finalize their ROLs before receiving any offer; (ii) the Multioffer DA, or M-DA, of which the DoSV procedure is an example; and (iii) our proposed Batched Multioffer DA, or BM-DA, which is similar to the M-DA but with early offers arriving on a predetermined day. We show that the BM-DA dominates the other two mechanisms in terms of student welfare. The reason is that early offers, by informing a student of the availability of certain programs, help her learn more efficiently. Moreover, we find that the student may do worse under the M-DA than under the DA because an early offer from an ex ante low-quality program may lead her to suboptimally accept it.

The comparison of the three mechanisms is further quantified in a set of simulations that use the same data from Germany. Relative to the DA, the BM-DA mechanism makes 72.2% of the students better off and only 20.8% worse off. The BM-DA also improves on the M-DA by making 41.7% of the students better off and 37.1% worse off.

Finally, our study reveals a previously unnoticed advantage of the program-proposing GS algorithm over the student-proposing version. Often, the latter is promoted because it is strategy-proof for students and achieves the student-optimal stable matching under the assumption that students have full information on their own preferences (see, e.g., Roth and Sotomayor, 1990). The above dynamic multioffer mechanisms instead rely on the program-proposing GS to generate early offers, so that offers in the process cannot be withdrawn later. By contrast, the student-proposing GS is incompatible with a multioffer mechanism because it allows each program only to *tentatively accept* a student before the algorithm concludes and thus does not generate offers until the very end.

Other related literature. Violations of the assumption that agents have full information on their own preferences have received little attention in the market design literature. As an exception, Narita (2018) finds that students reveal contradictory preferences in the main round and the subsequent round of school choice in New York City. Unlike our model, the author considers preference changes that are exogenous to the matching mechanism. Moreover, in the admissions to medicine programs in Germany, Dwenger, Kübler and Weizsäcker (2018) document results implying a more complex process of preference formation than is commonly assumed.

Costly acquisition of information about preferences is a recent topic in the matching literature. For example, Chen and He (2021a,b) theoretically and experimentally investigate students' incentives to acquire information about their own and others' preferences in school choice. These authors, as well as Artemov (2021), study the canonical DA and the Boston immediate-acceptance mechanisms. Similar to our paper, Immorlica et al. (2020) and Hakimov, Kübler and Pan (2021) investigate how advising students on their admission chances can facilitate information acquisition, although these studies focus on single-offer mechanisms such as the iterative implementations of the DA and investigate the provision of historic information. Informing students of their admission chances can also help students beyond preference discovery, as students in centralized school choice may have incorrect beliefs about their admission chances and thus adopt suboptimal application strategies (He, 2017; Kapor, Neilson and Zimmerman, 2020).

Sequential learning in our model is related to the theoretical literature on consumer search (Weitzman, 1979; Ke, Shen and Villas-Boas, 2016; Doval, 2018; Dzyabura and Hauser, 2019; Ke and Villas-Boas, 2019). In contrast to our setting, agents in that literature hold "offers" from all programs at the outset. The early-offer effect that we document resembles the increased demand for the item that is made salient in the model by Gossner, Steiner and Stewart (2021), although an early offer in our model changes an agent's behavior by informing her that the corresponding program is available.

Our study complements the recent literature on dynamic implementations of single-offer mechanisms. Under the assumption of full information on own preferences, a series of papers—some of which are motivated by university admission procedures in practice (Bó and Hakimov, 2018; Gong and Liang, 2020)—investigate dynamic (or iterative) versions of the DA mechanism (Echenique, Wilson and Yariv, 2016; Klijn, Pais and Vorsatz, 2019;

Bó and Hakimov, 2020).[6] Inspired by a university admission procedure used in France from 2009 to 2017, Haeringer and Iehlé (2021) study multiperiod admissions where a matching is computed in each period and students have the option to either finalize their matches or participate in the next period.

Our paper is also related to the literature on mechanism design with transferable utility where, in an initial stage, agents acquire information (e.g., Bergemann and Välimäki, 2002), make investments (e.g., Hatfield et al., 2014; Nöldeke and Samuelson, 2015), or face a surplus sharing rule (e.g., Dizdar and Moldovanu, 2016). The sequential information updates owing to early offers in our setup resemble those in open versus closed auctions (see, e.g., Compte and Jehiel, 2007).

The evolution of preferences in a decision process has been studied outside the market design literature. For example, Elster (1983) considers agents adjusting their preferences according to what is available to them, for which Alladi (2018) provides experimental evidence.

There is a large empirical literature on the determinants of college choice (for an early contribution, see, e.g., Manski and Wise, 1983), which investigates the determinants of preferences rather than the process of preference discovery. Early admission offers play an important role in college admissions in the United States (Avery, Fairbanks and Zeckhauser, 2003; Avery and Levin, 2010). Colleges seek to admit students who are enthusiastic about attending, and early admission systems give students an opportunity to signal their enthusiasm.

Organization of the paper. After introducing the institutional background of Germany's university admissions in Section 1, we proceed to the data analysis and present the results as well as robustness checks in Section 2. To explain the findings, Section 3 discusses several hypotheses and shows evidence from a survey. Section 4 develops a model of university admissions with preference discovery that can explain the observed early-offer effect. We present the BM-DA mechanism and compare the DA, the M-DA, and the BM-DA in a theoretical model and simulations. Finally, Section 5 concludes.

[6] One of the main findings in this literature is that agents are more likely to report their true preferences under a dynamic DA than under a static one. There is a growing literature showing that under the static DA, many agents do not report their true preferences in the laboratory (Chen and Sönmez, 2006; Rees-Jones and Skowronek, 2018; for a survey, see Hakimov and Kübler, 2021) and in the field (Artemov, Che and He, 2017; Shorrer and Sóvágó, 2017; Hassidim, Romm and Shorrer, 2021).

1 Institutional Background

1.1 University Admissions in Germany

Access to higher education in Germany is based on the principle that every student who completes the school track leading to the university entrance qualification (*Abitur*) should be given the opportunity to study in a university program of her choice. However, starting in the 1960s, a steep increase in the number of applicants created an overdemand for seats in programs such as medicine, so selection based on the final grade in the *Abitur* (numerus clausus) was introduced. In response to court cases brought forward against the universities, a central clearinghouse, the *Zentralstelle für die Vergabe von Studienplätzen* (ZVS), was established in 1972 to guarantee "orderly procedures."

In the 1990s and early 2000s, the number of programs administered through the ZVS clearinghouse steadily declined. The main reasons were that universities wanted to gain control of their admission process and that new bachelor's programs were created as part of the Bologna reforms in fields of study that were not required for participation in the ZVS. By 2005, the only programs administered by the ZVS were in the fields of medicine, pharmacy, dental medicine, veterinary medicine, and psychology (the latter only until 2010–11). Seats for these programs were allocated according to a procedure involving quotas regulated by law.[7] At the same time, severe congestion for many other programs emerged.

A reorganization and re-naming of the clearinghouse from ZVS to *Stiftung für Hochschulzulassung* (literally, Foundation for University Admission) was completed in 2008, and the DoSV, a new admission procedure for programs other than medicine and medicine-related subjects, was implemented in 2012. Universities have the option to participate in the DoSV, and they can do so for a subset of their programs. Since 2012, the number of programs participating in this procedure has increased steadily.[8]

[7] For analyses of the ZVS procedure, see Braun, Dwenger and Kübler (2010), Westkamp (2013), and Braun et al. (2014).

[8] For the winter term of 2015–16, 89 universities with 465 programs participated, compared with 17 universities with 22 programs in the first year in which the DoSV was implemented (winter term of 2012–13). The total number of students who were assigned to a program through the DoSV in 2015–16 was 80,905, relative to a total of 432,000 students who started university in Germany that year.

1.2 The DoSV: A Multioffer Procedure

The DoSV procedure has multiple phases. The early phases extend over several weeks and allow for student-program interactions that resemble those in a decentralized market. Each student applies to up to 12 programs and forms an ROL, without the possibility of later adding other programs to this list. Importantly, a student is not required to finalize her ROL until a later date, by which she may have received some offers from the programs to which she applied. With the finalized ROLs, the program-proposing GS algorithm is run to determine the matching. This procedure provides us with a unique data set of offers to students, their reranking of programs, and offer acceptances and rejections in real time. It allows us to measure the effects of early offers on the final admission outcome.

Figure 1 describes the timeline of the DoSV. The dates indicated are relevant for the winter term and are the same every year. We use data from the winter term, since admission for the summer term is possible only for a small number of programs. The procedure consists of the following phases.

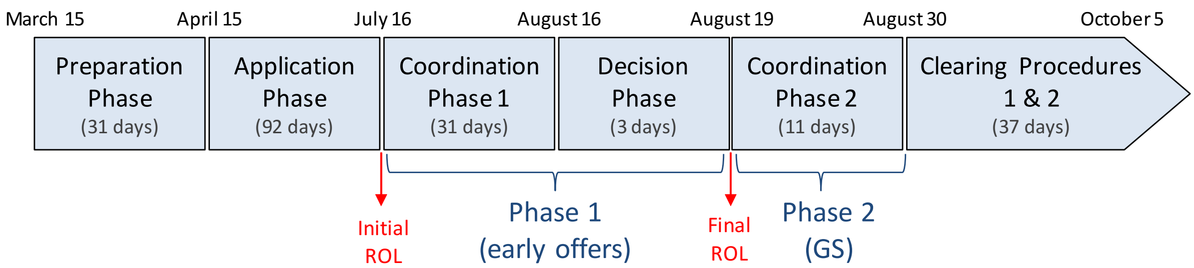


Figure 1 – Timeline of the DoSV Procedure (Winter Term)

Notes: Our main interest is in Phase 1—consisting of Coordination Phase 1 and the Decision Phase—where early offers are made and in Phase 2—consisting of Coordination Phase 2—where the Gale-Shapley (GS) algorithm is run.

Preparation Phase (March 15–April 14): The participating university programs register with the clearinghouse.

Application Phase (April 15–July 15): Students apply to at most 12 programs by directly submitting their application to the universities. The universities transmit to the clearinghouse the applications they have received for their programs. By default, the programs in a student's ROL are ordered according to the arrival time of the corresponding applications at the clearinghouse. Students can, however, actively modify their ROL at any point during this phase. No new applications can be submitted after this phase, and no program will consider a student who did not apply to it.

Coordination Phase 1 (July 16–August 15): The programs rank applicants following a quota system. The size, number, and nature of the quotas are determined by state laws and regulations and by the universities themselves.[9] For each program, the university admissions office creates rankings over its applicants—one for each quota—and transmits them to the clearinghouse. Every applicant is considered and ranked for every quota.[10] Given the legal restrictions, universities have only very limited scope for strategic manipulation of their rankings of applicants,[11] although they may have some control as to when the lists are transmitted. Via automated emails, the clearinghouse sends admission offers for a program to its top-ranked students up to the program's capacity under each quota. We define these offers as *early offers*. Note that an early offer cannot be rescinded and does not expire until August 29 (the end of coordination Phase 2). A student with one or more offers may accept one of them and leave the procedure, or she can choose to hold on to these offers (either all of them or a subset). If an offer is rejected, a new offer to the next applicant in that program's ranking is automatically generated. Students are informed about how a program ranks them in each quota, the total number of seats available in the program, and the number of students ranked above them in each quota who are no longer competing for a seat.

Decision Phase (August 16–18): Starting on August 16, university programs can no longer submit their rankings of applicants to the clearinghouse. However, early offers continue to be generated until August 18 because students may still reject offers received in coordination Phase 1. Students are encouraged to finalize their ROL.

Coordination Phase 2 (August 19–29): At the beginning of this phase, a program may have (a) seats taken by students who have accepted its early offer and left the procedure, (b) seats/offers tentatively held by students who have kept their early offer from this

[9]The main quotas are (i) the *Abitur* Quota (*Abiturbestenquote*), where the ranking is based on a student's average *Abitur* grade; (ii) the Waiting Time Quota (*Wartezeitquote*), which gives priority to applicants who have waited for the greatest number of semesters since obtaining the *Abitur*; and (iii) the University Selection Quota (*Auswahlverfahren der Hochschulen*), which employs criteria that are determined by the universities themselves. Details on the process through which programs rank applicants and the role of quotas are provided in Appendix A.1. These quotas are filled simultaneously, unlike in the old procedure for medical programs (see footnote 3).

[10]For this reason, we sometimes consider a student's most favorable quota at a program under which she has the highest probability of receiving an offer. A student cannot receive two offers from a program even if they are from different quotas.

[11]The *Abitur* and Waiting Time Quotas rely on nonmanipulable criteria, while the ranking under the University Selection Quota is in practice almost entirely determined by students' *Abitur* grade. In our data, the average correlation coefficient between the rankings under the *Abitur* Quota and the University Selection Quota is 0.86 across programs.

program but have chosen to stay on, and (c) seats available because of its rejected early offers. Meanwhile, a student may have (i) left the procedure by accepting an early offer, (ii) kept an early offer and chosen to stay on with her final ROL, (iii) received no offer and stayed on with her final ROL, or (iv) exited the procedure, thereby rejecting all offers. Taking the remaining students and the seats available or tentatively held, the clearinghouse runs a program-proposing GS algorithm as follows:

1. Following the ranking of its applicants provided in coordination Phase 1, a program sends admission offers to students ranked at the top of its ranking up to the number of available seats that are not tentatively held. However, the students who previously received an offer from the program can never receive the same offer again.

2. Students with multiple offers keep the highest-ranked one according to their final ROLs and reject all other offers. All other students are inactive.

3. Steps 1 and 2 are repeated until every program either has no seats left or has no more students to make offers to. Then each student is assigned to the program she holds, if any.

This phase uses the program-proposing GS algorithm where students start out with their highest-ranked offer from previous phases. They can never do worse than this offer, while a better offer may arrive. We define the GS algorithm as a computer code that uses information on students and programs to calculate a matching outcome. Importantly, the GS algorithm is silent about how students and programs provide such information. See Appendix D.1 for more details and the definition of the GS algorithm.

Clearing Phases 1 and 2 (August 30–September 4; September 30–October 5): A random serial dictatorship is run to allocate the remaining seats to students who have not yet been admitted.

For the analysis of students' choices, we focus on Coordination Phase 1 and the Decision Phase. Since the two phases do not differ from the students' perspective, we group them together and call them Phase 1 (see Figure 1). Coordination Phase 2 is also of interest, and we call it Phase 2. Recall that offers in Phase 1 are early offers. We define *initial ROL* as the ROL over programs that the clearinghouse has recorded for each student at the beginning of Phase 1, while the ROL at the end of Phase 1 is defined as the *final ROL*. A program is defined as *feasible* to a student if the student applied to the program and was ranked higher than the lowest-ranked student who received an offer from the program in coordination Phase 2.[12] A student may not actually receive an offer from a feasible program, as she might have left the procedure before she could receive the offer.

In contrast to single-offer mechanisms that typically deliver at most one offer to a student, the DoSV is a dynamic multioffer mechanism because a student may hold multiple offers in Phase 1. Hence, we call this phase the multioffer phase.

1.3 Data

Our data set covers the DoSV procedure for the winter term of 2015–16. There are 183,088 students who applied to 465 programs at 89 universities in total. The data contain students' sociodemographic information (gender, age, postal code) and their *Abitur* grade.[13] Furthermore, we observe students' ROLs at any point in time, the programs' rankings of applicants, the offers made by the programs throughout the procedure, the acceptance and rejection of offers by students, and the final admission outcome.

We exclude students with missing sociodemographic information as well as those who apply to specific programs with complex ranking rules. These are mostly students who want to become teachers and have to choose multiple subjects (e.g., math and English). For our analysis, we focus on the subsample of students who apply to at least two feasible programs and accept an offer. This leaves us with 21,771 students.

Table 1 provides summary statistics. On average, applicants to standard programs apply to 2.9 programs (column 1). The corresponding figure is 4.2 among the 59% of students who apply to more than one program (column 2) and 4.7 among those who apply to at least two feasible programs and accept an offer (column 3). Panel C reveals that 58.1% of students who apply to at least two programs (column 2) have at least one feasible program; that is, they would have received at least one offer in the course of the procedure if they had not exited before Phase 2. Importantly for our analysis, more than half of the students who apply to more than one program receive one or more offers in

[12] Our definition of feasibility is conditional on a student applying to a program. By contrast, the definition of feasibility in other papers on school choice and university admissions (e.g., Fack, Grenet and He, 2019) extends to the programs that a student did not apply to. This alternative is less appropriate in our setting because not all programs participate in the clearinghouse and our analysis is conditional on the programs to which each student has applied.

[13] In the data, the *Abitur* grade is missing for about half of the students, but we can infer it for approximately two-thirds of applicants with a missing grade based on how students are ranked under the programs' *Abitur* quota. See Appendix A.1 for details.

Table 1 – Summary Statistics of DoSV Application Data for 2015-16 (Winter Term)

	Sample		
	All applicants to standard programs	Applied to more than one program	Applied to at least two feasible programs and accepted an offer
	(1)	(2)	(3)
A. Students			
Female	0.579	0.596	0.558
Age	20.8	20.5	20.7
	(3.2)	(2.6)	(3.1)
Abitur percentile rank (between zero and one)	0.50	0.51	0.65
	(0.29)	(0.29)	(0.28)
B. Applications			
Length of initial ROL (on July 15)	2.9	4.2	4.7
	(2.6)	(2.7)	(2.9)
Reranked programs before Phase 1[a]	0.537	0.209	0.298
Reranked programs during Phase 1[b]	0.178	0.305	0.419
Fraction of programs located in student's municipality	0.205	0.153	0.184
	(0.379)	(0.311)	(0.342)
Fraction of programs located in student's region (*Land*)	0.623	0.610	0.583
	(0.446)	(0.420)	(0.417)
Average distance to ranked programs (km)	111	120	126
	(127)	(119)	(122)
Top-ranked program (on July 15)—field of study[c]			
Economics and business administration	0.368	0.397	0.427
Psychology	0.197	0.204	0.138
Social work	0.121	0.110	0.044
Law	0.110	0.125	0.170
Math/engineering/computer science	0.065	0.052	0.097
Natural sciences	0.055	0.046	0.059
Other	0.085	0.065	0.066
C. Feasible programs and offers received			
At least one feasible program	0.505	0.581	1.000
Received one or more early offers in Phase 1	0.475	0.549	0.989
D. Admission outcome			
Canceled application before Phase 2	0.054	0.042	0.000
Accepted an early offer in Phase 1	0.220	0.247	0.554
Not initially top ranked	0.262	0.399	0.369
Participated in Phase 2	0.725	0.711	0.446
Accepted an offer in Phase 1 or Phase 2	0.448	0.518	1.000
Number of days between offer arrival and acceptance	9.19	9.62	9.11
	(8.73)	(8.75)	(8.30)
Number of students	110,781	64,876	21,711

Notes: Summary statistics are computed from the DoSV data for the winter term of 2015–16. The main sample (column 1) is restricted to students with nonmissing values and excludes those who applied to specific multi-course programs (*Mehrfachstudiengang*), which consist of two or more subprograms with complex assignment rules. Column 2 further restricts the sample to students who applied to two programs or more. Column 3 considers students who applied to at least two feasible programs and either actively accepted an early offer during Phase 1 or were assigned to a program through the computerized algorithm in Phase 2. For "*Abitur* percentile rank," a higher value indicates a better Abitur grade. The distance between a student's home and a program is computed as the Cartesian distance between the centroid of the student's postal code and the geographic coordinates of the university in which the program is located. The number of days elapsed between offer arrival and acceptance is the number of days between the date the offer that was ultimately accepted was made to a student and the date it was accepted; for students who were assigned to their best offer by the computerized algorithm in Phase 2, the acceptance date is set to the first day of Phase 2——i.e., August 19, 2015. Standard deviations are shown in parentheses.

[a] A student is considered as having reranked programs before Phase 1 if she applied to only one program or if she manually altered the ordering of her applications before July 15.

[b] A student is considered as having reranked programs during Phase 1 if either the final ROL is different from the initial ROL or the student accepted an early offer from a program that she did not initially rank in first position.

[c] For programs combining multiple fields of study, each field is assigned a weight of $1/k$, where k represents the number of fields.

Phase 1, and around one-quarter (24.7%) accept an offer in Phase 1 (Panel D). Among them, almost 40% accept an offer that was not their first choice in their initial ROL. Table 1 also indicates that only half of the students end up accepting an offer from a program in either Phase 1 or Phase 2.[14] The rest may have accepted offers from programs that did not participate in the DoSV procedure.

1.4 Timing of Activities in the DoSV 2015–16

Figure 2 presents an overview of the activities in the DoSV procedure for 2015–16. It displays the points in time when students register with the clearinghouse, when they submit an ROL that is not changed any more ("finalize their ROL"), when they receive their first offers from programs ("receive an offer"), and when they exit the procedure. An important takeaway is that the first offers received by students are spread out over Phase 1 (see also Appendix Figure B1). It is exactly this dispersed arrival of offers that allows us to identify the effect of early offers on offer acceptance. We show below that the offer arrival is not correlated with students' initial ROLs and that early offers are not, on average, made by more selective or desirable programs. Instead, the time at which programs submit their rankings to the clearinghouse is determined by administrative processes within the universities.[15]

Almost all student exits from the DoSV take place in phases 1 and 2. During Phase 1, students leave when they either accept an offer or cancel all applications. The number of exits peaks at the beginning of Phase 2 when the clearinghouse automatically accepts an early offer from the top-ranked program of students who have not actively accepted the offer. The second spike occurs at the end of this phase, indicating that around half of the students do not receive any offer and therefore remain in the procedure until the very end.

Next, we disaggregate the exits by their reason for leaving the procedure. Figure 3 shows that 22% of students actively accept an offer during Phase 1, 22% receive their best offer during Phase 2 when the GS algorithm is run (of which two-thirds are automatically removed on the first day because they have an offer from their top-ranked program), 14%

[14]Throughout the analysis, a student is defined as having accepted an offer when she either actively accepts an early offer in Phase 1 or is assigned by the computerized algorithm in Phase 2.

[15]According to the *Stiftung für Hochschulzulassung*, the time point when the rankings are transmitted to the clearinghouse depends on the number of personnel available in an admissions office, the number of programs a university administers through the DoSV, the number of incomplete applications received, internal processes to determine the amount of overbooking for each program, and a university's policy as to whether to check all applications for completeness or instead to accept applicants conditionally.

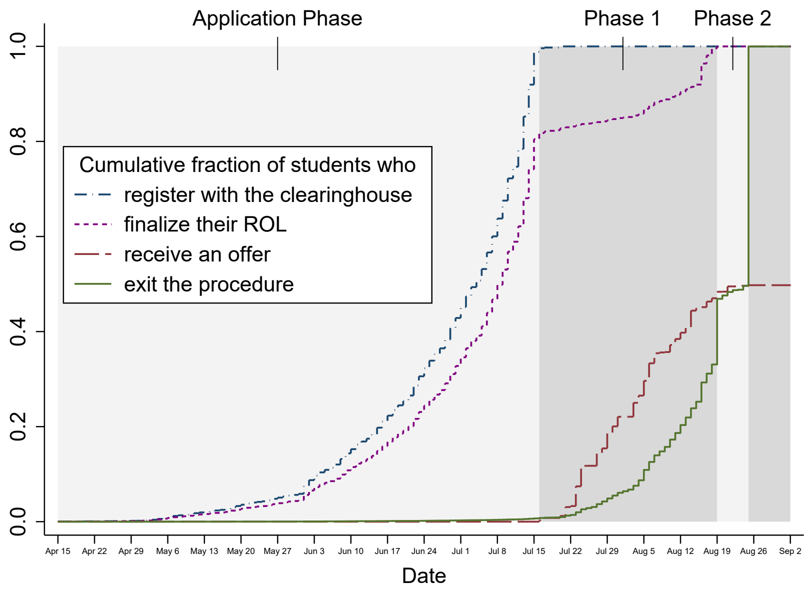


Figure 2 – Activities during the DoSV Procedure (Winter Term of 2015–16)

Notes: This figure displays the evolution of several key indicators throughout the DoSV procedure for the winter term of 2015–16: (i) cumulative fraction of students who register with the clearinghouse during each phase (dash-dottted line), (ii) cumulative fraction of students who finalize their ROL of programs (short-dashed line), (iii) cumulative fraction of students who receive at least one offer (long-dashed line), and (iv) cumulative fraction of students who exit the procedure (solid line) due to one of the following motives: active acceptance of an early offer during Phase 1, automatic acceptance of the best offer during Phase 2, cancellation of application, rejection due to application errors, or rejection in the final stage for students who participate in Phase 2 but receive no offer.

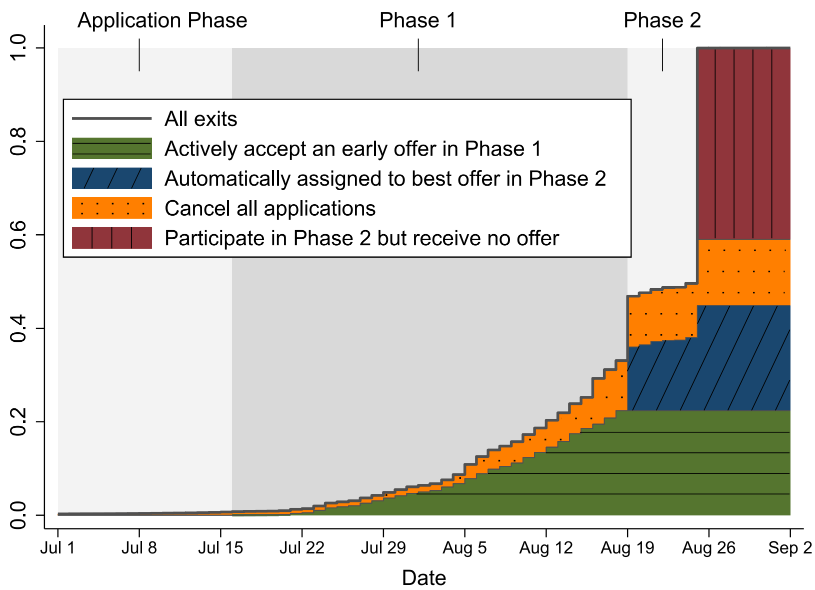


Figure 3 – Reasons for Exiting the DoSV Procedure (Winter Term of 2015–16)

Notes: This figure shows the cumulative admission outcomes of students throughout the DoSV procedure for the winter term of 2015–16: (i) cumulative fraction of students who actively accept an early offer received during Phase 1 (area with horizontal hatching), (ii) cumulative fraction of students on whose behalf the clearinghouse accepts their best offer during Phase 2 (area with diagonal hatching), (iii) cumulative fraction of students who cancel all applications (dotted area), and (iv) cumulative fraction of students who participate in Phase 2 but receive no offer (area with vertical hatching).

cancel their applications at some point, while the remaining 41% participate in Phase 2 but receive no offer.

2 Accepting Early Offers: Empirical Results

We now turn to the question of whether a program's offer to a student is more likely to be accepted when it is an early offer. Our analysis is restricted to a student's feasible programs. Recall that a program is feasible to a student if the student applied to the program and would have received its offer, provided that she remained in the procedure until Phase 2 while holding other students' behavior constant. Infeasible programs are irrelevant to a student's offer acceptance decision. If offers from the feasible programs arrive in an exogenous sequence, common matching models predict no early-offer effect on acceptance because of the assumption that students have full information on their own preferences.

2.1 Empirical Approach

We adopt a logit model to assess whether students are more likely to accept early offers. Let F_i represent student i's set of feasible programs, with the programs being indexed by j. For j in F_i:

$$U_{i,j} \quad = \quad \boldsymbol{Z}_{i,j}\beta + \epsilon_{i,j},$$

where $U_{i,j}$ representes how student i values feasible program j at the time of making the ranking or acceptance decision, $\boldsymbol{Z}_{i,j}$ is a row vector of student-program-specific characteristics, and $\epsilon_{i,j}$ is independent and identically distributed (i.i.d.) according to a type I extreme value (Gumbel) distribution. Note that $U_{i,j}$ may not be i's true, full information utility but rather stands for i's valuation of j conditional on all her information at the time of the decision.

Students accept the offer from their most preferred feasible program. Therefore, we can write i' choice probability for $j \in F_i$ as

$$\begin{aligned}
&\mathbb{P}\left(i \text{ accepts program } j\text{'s offer} \mid F_i, \{\boldsymbol{Z}_{i,j}\}_{j \in F_i}\right) \\
&\quad = \mathbb{P}\left(U_{i,j} \geqslant U_{i,j'}, \forall j' \in F_i \mid F_i, \{\boldsymbol{Z}_{i,j}\}_{j \in F_i}\right) = \frac{\exp\left(\boldsymbol{Z}_{i,j}\beta\right)}{\sum_{j' \in F_i} \exp\left(\boldsymbol{Z}_{i,j'}\beta\right)}. \qquad (1)
\end{aligned}$$

In effect, our analysis assumes that a student ranks her most preferred feasible program above all other feasible programs in her final ROL, conditional on the set of applications that were already finalized in the Application Phase.[16] By focusing on feasible programs, we allow for the possibility that a student arbitrarily ranks an infeasible program without any payoff consequences (Artemov, Che and He, 2017; Fack, Grenet and He, 2019).

To investigate whether receiving an early offer from program j in Phase 1 (as opposed to receiving it in Phase 2) increases the probability that i accepts j's offer, the model is specified as

$$U_{i,j} = \theta_j + \delta\, \mathit{EarlyOffer}_{i,j} + \gamma d_{i,j} + \boldsymbol{X}_{i,j}\lambda + \epsilon_{i,j}, \qquad (2)$$

where θ_j represents the fixed effect of program j and $d_{i,j}$ represents the distance between student i's postal code and the address of the university where the program is located. $\mathit{EarlyOffer}_{i,j}$ is a dummy variable that equals one if i receives a *potential* early offer from program j during Phase 1 (i.e., up to August 18) rather than in Phase 2. A potential early offer is defined as either an offer that was actually received by the student in Phase 1 or—if the student canceled her application to the program before Phase 2—an offer that the student would have received in Phase 1.[17] The row vector $\boldsymbol{X}_{i,j}$ includes other student-program-specific controls. The coefficient of interest, δ, is thus identified by the variation in the timing of the offer arrival across students and programs, conditional on the programs' observed heterogeneity and unobserved average quality.

[16] As the DoSV is based on the program-proposing GS algorithm, it is not strategy-proof for students. A student can misreport her preferences in an ROL by "reversal" (i.e., reversing the true preference order of two programs) and "dropping" (i.e., dropping programs from the true preference order). To identify profitable misreports, a student usually needs rich information on other students' and programs' preferences. In a low-information environment, Roth and Rothblum (1999) show that reversals are not profitable. Dropping does not create an issue for our analysis because we focus on the programs ranked in an ROL.

[17] Our focus on *potential* rather than *actual* early offers ensures that our definition of an early offer does not depend on the student's acceptance decision. In the data, 90% of potential early offers were actually received by students.

2.2 Identifying Assumption: Exogenous Arrival of Offers

One potential concern is that early offers might be more attractive than those arriving later for reasons unrelated to their arrival time. The specification in Equation (2) requires that $EarlyOffer_{i,j}$ is independent of shocks ($\epsilon_{i,j}$) conditional on other controls. To test this identifying assumption, we examine whether the average quality of potential offers varies over time using two measures of a program's selectivity and desirability. After calculating these measures for every program, we take the average over all offers that are sent out on a given day (weighted by the number of offers made by each program).

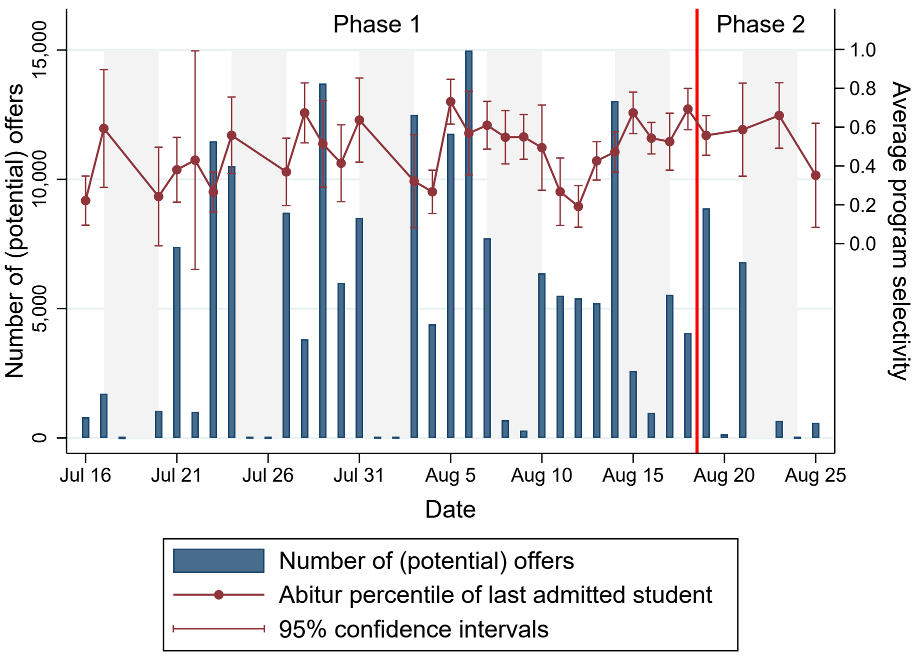
In Panel A of Figure 4, the selectivity measure is the *Abitur* percentile (between zero and one, with a higher value indicating a higher selectivity) of the last student admitted to the program in Phase 2, with the percentile computed among all DoSV applicants. A higher value on this measure indicates a higher degree of selectivity. In Panel B, similar to Avery et al. (2013), a program's desirability is inferred from students' acceptance decisions among their feasible programs. Specifically, we estimate the conditional logit model described in Equation (2) and use the program fixed effect estimates (standardized to have a mean of zero and a unit variance across programs) as a proxy for program desirability.[18]

In either of the two figure panels, there is no clear pattern over time, which is consistent with the timing of offers being determined mostly by the universities' administrative processes rather than by strategic considerations. If anything, the very early offers tend to come from slightly less selective or less desirable programs.

We further investigate time trends in offers based on regression analyses. Column 1 of Table 2 (Panel A) shows an insignificant correlation between the selectivity measure on each day and the number of days that have elapsed since the start of Phase 1. Column 3 repeats the same regression for the desirability measure. The correlation is positive and significant, implying that earlier offers are from marginally less desirable programs. Columns 2 and 4 regress the selectivity measures on week dummies. Indeed, the results

[18] We use the results in column 3 of Table 3, in which we control for a quadratic function of distance to the program, whether the program is in the student's region (*Land*), and how the program ranks the student. We also considered an alternative measure of program desirability based on students' initial ROLs rather than on their acceptance decisions, using a larger sample of students who applied to at least two programs (not necessarily feasible). The results are very similar to those based on students' acceptance decisions. Although positive and statistically significant, the correlation between the two measures of program selectivity and desirability is small (0.17), suggesting that these proxies capture different dimensions.

A. Program selectivity: *Abitur* percentile of last admitted applicant



B. Program desirability: based on students' acceptance decisions

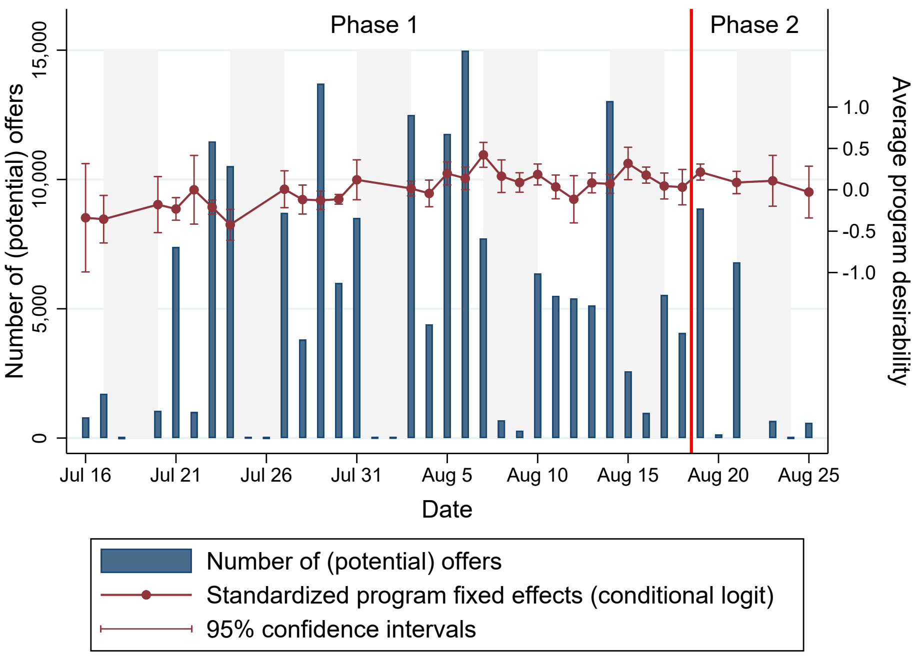


Figure 4 – Offer Arrival, Program Selectivity, and Program Desirability

Notes: Vertical bars indicate the number of potential offers sent out by programs on a given day throughout the DoSV procedure (winter term of 2015–16). Potential offers are defined as either actual offers that were sent out to students or offers that a student would have received had she not canceled her application to the program. The jagged line shows the average selectivity/desirability of programs sending out offers on a given day, with 95% confidence intervals denoted by vertical T bars. In Panel A, a program's selectivity is proxied by the *Abitur* percentile (between zero and one, with a higher value indicating a higher selectivity) of the last student admitted to the program in Phase 2. In Panel B, a program's desirability is proxied by the program fixed effect estimates (standardized to have a mean of zero and a unit variance across programs) from the conditional logit model whose results are shown in column 3 of Table 3. The selectivity/desirability of potential offers made on a given day is computed as the average over the programs making these offers on a given day (weighted by the number of offers made by each program). The measures are not shown for days in which fewer than 150 potential offers were made, which mostly coincide with weekends (denoted by gray-shaded areas).

Table 2 – Offer Arrival, Program Selectivity, and Program Desirability: Regression Analyses

	Program selectivity: *Abitur* percentile of last admitted applicant		Program desirability: Based on students' acceptance decisions	
	(1)	(2)	(3)	(4)
A. Dependent variable: average selectivity/desirability of programs making offers on a given day				
Days since start of Phase 1	0.0038		0.0133***	
	(0.0024)		(0.0028)	
Week of (potential) offer arrival				
Week 1 (July 16–22)		−0.110		−0.294***
		(0.104)		(0.061)
Week 2 (July 23–29)		−0.052		−0.248***
		(0.116)		(0.088)
Week 3 (July 30–August 5) (reference week)		.		.
		(.)		(.)
Week 4 (August 6–12)		−0.028		0.090
		(0.119)		(0.088)
Week 5 (August 13–19)		0.027		0.053
		(0.103)		(0.064)
Week 6 (August 20–25)		0.066		0.011
		(0.101)		(0.056)
B. Dependent variable: variance of selectivity/desirability of programs making offers on a given day				
Days since start of Phase 1	0.0008		0.0029	
	(0.0006)		(0.0034)	
Week of (potential) offer arrival				
Week 1 (July 16–22)		−0.020		−0.198
		(0.020)		(0.119)
Week 2 (July 23–29)		−0.008		−0.199
		(0.017)		(0.119)
Week 3 (July 30–August 5) (reference week)		.		.
		(.)		(.)
Week 4 (August 6–12)		0.005		−0.008
		(0.024)		(0.197)
Week 5 (August 13–19)		−0.005		−0.158
		(0.018)		(0.118)
Week 6 (August 20–25)		0.067***		−0.199
		(0.023)		(0.118)
N (days in Phase 1)	39	39	39	39
Number of potential offers	192,840	192,840	192,840	192,840

Notes: This table reports linear regression estimates to test whether the timing of offers is correlated with the selectivity (columns 1, 2) or desirability (columns 3, 4) of the programs sending out these offers. The sample includes all potential offers, i.e., offers that either were sent out to students or could have been sent out had the students not canceled their application to the program. The day of arrival of each (potential) offer is identified as the day it became feasible to the student. In columns 1 and 2, a program's selectivity is proxied by the *Abitur* percentile (between zero and one, with a higher value indicating a higher selectivity) of the last student admitted to the program in Phase 2. In columns 3 and 4, a program's desirability is proxied by the program fixed effect estimates (standardized to have a mean of zero and a unit variance across programs) from the conditional logit model whose results are shown in column 3 of Table 3, using the sample of students who applied to at least two feasible programs and accepted an offer. After calculating the selectivity/desirability measures for every program, we compute the mean and variance of each measure over all offers that were sent out on a given day (weighted by the number of offers made by each program). In columns 1 and 3, the program selectivity/desirability measures are regressed on a linear time trend; in columns 2 and 4, they are regressed on a vector of week dummies, with the third week of the DoSV procedure (July 30–August 5) as the omitted category. Standard errors clustered at the day level are shown in parentheses. ***: $p < 0.01$.

show that the very early offers are less desirable. Panel B further investigates time trends in the variance of the selectivity/desirability of offers, since the higher acceptance rate of early offers may be caused by their more dispersed quality relative to later offers (even though the average quality is the same). We find no evidence of such trends: the coefficients on days elapsed or week dummies are almost never statistically significant.

Additionally, in Table 4 (columns 1–3) we show that early offers are not correlated with how students rank feasible programs in their initial ROLs. Taken together, the results indicate that programs from which students receive early offers are not more attractive and that they were initially not ranked higher by students.

2.3 Empirical Results on the Early-Offer Effect

We use the sample of students who applied to at least two feasible programs and either actively accepted an early offer in Phase 1 or were assigned by the GS algorithm in Phase 2. In the empirical analysis, we refer to these students as having *accepted* a program's offer. In total, there are 21,711 such students. Together, they applied to 66,263 feasible programs.

We start with the specification in Equation (2) to study the impact of early offers on the acceptance of offers. The regression results are reported in Table 3. Column 1 includes the early-offer dummy (*EarlyOffer*) and program fixed effects. The program fixed effects capture observed and unobserved program-specific characteristics, such as selectivity or faculty quality, which might be correlated with students' offer acceptance decisions. The coefficient on *EarlyOffer* is positive and significant, suggesting that having received an early offer increases the probability of a student accepting that offer. Column 2 adds another dummy variable that is equal to one for the first early offer (*FirstEarlyOffer*).[19] Students are even more likely to accept the first offer, while all early offers remain more likely to be accepted than other offers. The results are qualitatively similar when we add further controls, such as a quadratic function of distance to the program and whether the program is in the student's region (*Land*) (column 3), how the program ranks the student (column 4),[20] and the chances of a student not receiving an offer from the program in

[19] In our sample, the average time between the first and second early offers is 4.89 days among the 17,351 students who received two or more early offers. When we consider the 19,582 students who received or could have received two or more early offers, the average time between the first and second (potential) early offers is 5.38 days.

[20] We compute how a student is ranked by a given program using the student's percentile (between zero and one, with a higher value indicating a better rank) among all applicants to the program under the *Abitur* quota.

Phase 2 (column 5). We proxy the last control variable by the ratio between a student's rank and the rank of the last student who received an offer from the program in Phase 1. The variable is zero if a student has an early offer from the program. We thus allow for the possibility that a student accepts an early offer because she does not expect to receive other offers in Phase 2.

All these results show a positive early-offer effect on offer acceptance and a larger effect for the first early offer. To quantify the effects, we calculate the impact of an early offer on the probability of offer acceptance (Table 3, Panel B). On average, a feasible program is accepted by a student with a probability of 0.385. An early offer that is not the first one increases the acceptance probability by 8.7 percentage points, or 27.9%, based on the estimates in column 5.[21] This is of the same order of magnitude as the estimates from other specifications (columns 1–4). The first early offer has a larger marginal effect. It increases the acceptance probability by 11.8 percentage points, or 38.3%, based on the estimates in column 5.[22]

Another way to evaluate the magnitude of the early-offer effect is to use distance as a numeraire (Table 3, Panel C). At the sample mean of distance (126 km, as shown in column 3 of Table 1), an early offer that is not the first offer gives the program a boost in utility equivalent to reducing the distance by 61 km, based on the results in column 5.[23] The first early offer has an even larger effect, amounting to a reduction of 79 km.

We explore the heterogeneity of the early-offer effect by adding interactions between student characteristics and the *EarlyOffer* and *FirstEarlyOffer* dummies. The results are shown in Appendix Table B1. They indicate that female students respond less to early offers, although there is no additional heterogeneity in the effect of the first early offer. Students with a better *Abitur* grade are less responsive to the first early offer but do not behave differently for other early offers. The number of feasible programs that a student has does not change the early-offer and first-early-offer effects.

[21]This marginal effect is the difference between the following two predictions on offer acceptance: while keeping all other variables at their original values, we let (i) $\mathit{EarlyOffer} = 1$ and $\mathit{FirstEarlyOffer} = 0$ and (ii) $\mathit{EarlyOffer} = \mathit{FirstEarlyOffer} = 0$. The baseline probability is the average of the second prediction across students, while the reported marginal effect is the average difference between the two predictions across students. The marginal effect of the first early offer is calculated in a similar manner.

[22]When we further include the dummies for the second and third early offers, we find that their marginal effects decrease monotonically in the arrival order.

[23]To calculate the marginal effect of this nonfirst early offer, we calculate the reduction in distance from 126 km that is needed to equalize the effect on utility of switching *EarlyOffer* from one to zero. A similar calculation is performed for the marginal effect of the first early offer.

Table 3 – Early Offer and Acceptance among Feasible Programs: Conditional Logit

	(1)	(2)	(3)	(4)	(5)
A. Estimates					
EarlyOffer: Potential offer from program in Phase 1	0.484***	0.410***	0.411***	0.404***	0.424***
	(0.041)	(0.043)	(0.044)	(0.044)	(0.108)
FirstEarlyOffer: First offer in Phase 1		0.133***	0.147***	0.147***	0.147***
		(0.022)	(0.023)	(0.023)	(0.023)
Distance to university (thousands of km)			−9.36***	−9.37***	−9.37***
			(0.33)	(0.33)	(0.33)
Distance to university squared			12.52***	12.54***	12.54***
			(0.55)	(0.55)	(0.55)
Program in student's region (*Land*)			−0.005	−0.006	−0.006
			(0.039)	(0.039)	(0.039)
Program's ranking of student (between zero and one)				0.439*	0.442*
				(0.227)	(0.227)
Chances of not receiving an offer from program in Phase 2					0.016
					(0.076)
Program fixed effects (376 programs)	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263
B. Marginal effects on acceptance probability of feasible programs					
Baseline (no early offer) acceptance probability: 38.5%					
Nonfirst early offer (percentage points)	10.4	8.7	8.4	8.3	8.7
	(1.5)	(1.4)	(1.6)	(1.5)	(1.6)
First early offer (percentage points)		11.6	11.5	11.3	11.8
		(1.7)	(2.0)	(2.0)	(2.1)
C. Marginal effects on utility (measured in distance)					
Average distance to ranked programs: 126 km					
Nonfirst early offer (in km)			−59	−58	−61
First early offer (in km)			−78	−77	−79

Notes: This table reports estimates from a conditional logit model for the probability of accepting a program among feasible programs. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., the programs from which she could have received an offer by the end of Phase 2. A program's ranking of the student is computed as the student's percentile (between zero and one, with a higher value indicating a better rank) among all applicants to the program under the *Abitur* quota. The chances of not receiving an offer from a program in Phase 2 are proxied by the ratio between the student's rank and the rank of the last student who received an offer from the program in Phase 1; the variable is zero if the student has an early offer from the program. In Panel B, for the marginal effect of a nonfirst early offer on offer acceptance probability, we measure the difference between the following two predictions on offer acceptance behavior: while keeping all other variables at their original values, we let (i) *EarlyOffer* = 1 and *FirstEarlyOffer* = 0 and (ii) *EarlyOffer* = *FirstEarlyOffer* = 0. The baseline probability is the average of the second prediction across students, while the reported marginal effect is the average of the difference between the two predictions across students. The marginal effect of the first early offer is calculated in a similar manner. In Panel C, the marginal effect of a nonfirst early offer measured in distance is calculated as the reduction in distance from 126 km that is needed to equalize the effect on utility of switching *EarlyOffer* from one to zero. A similar calculation is performed for the marginal effect of the first early offer. Standard errors are shown in parentheses. *: $p<0.1$; ***: $p<0.01$.

Early-offer effect on students' reranking behavior. We extend the above analyses to students' reranking behavior, which is possible because our data record all changes in a student's ROL. Specifically, we use the initial and final ROLs of each student to investigate whether the ranking of programs is influenced by early offers.

As justified in Section 2.1, we restrict our attention to feasible programs and extract information from a final ROL as follows: (i) for a student who actively accepted an early offer during Phase 1, we code only that she prefers the accepted offer to all other feasible programs in her ROL (clearly, we do not have credible information on the relative rank order among all the feasible programs); (ii) for a student who was assigned to a program in Phase 2, we use the rank order among the feasible programs in her final ROL up to the first program that made her an early offer in Phase 1. Programs ranked below this highest-ranked early offer are coded only to be less preferred than those ranked above. Their relative rank order is ignored because it is payoff-irrelevant for the student.

Using a rank-ordered logit (or exploded logit), we obtain the results in Panel A of Table 4. Columns 1–3 are placebo tests in which we use a student's initial ROL as the outcome variable. The results show that there is no significant correlation between the initial rank order of a program and receiving an early offer from that program, which is consistent with the finding that early offers are not from more attractive programs.

Columns 4–6 reveal that receiving an early offer induces a student to rank that program higher in her final ROL. Similarly, the first early offer enjoys a premium.

Using the estimation results, we further quantify the effect of receiving an early offer and find results that are almost identical to those for acceptance probability (Table 3). Panel B of Table 4 presents the marginal early-offer effects on the probability of top ranking the program in one's ROL among feasible programs. A nonfirst early offer increases the probability of top ranking the program by 8–10 percentage points, or 25–30% (columns 4–6).[24] The first early offer has a larger effect. It increases the probability of top ranking the program by 11 percentage points, or 33–36% (columns 5, 6).

In Panel C of Table 4, at the sample mean of distance (126 km), the first early offer gives the program a boost in utility that is equivalent to reducing the distance by 76 km, while the distance-equivalent utility of other early offers is a reduction of 60 km on average.

Robustness checks. Our results are robust to a number of sensitivity tests.

[24]The calculations are similar to those on offer acceptance probability. See the details in footnote 21.

Table 4 – Initial vs. Final Ranking of Feasible Programs: Rank-Ordered Logit

	Rank-order list					
	Initial ROL (at start of Phase 1)			Final ROL (at end of Phase 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Estimates						
EarlyOffer: Potential offer from program in Phase 1	−0.033	−0.028	−0.071	0.453***	0.387***	0.405***
	(0.028)	(0.028)	(0.078)	(0.040)	(0.042)	(0.105)
FirstEarlyOffer: First offer in Phase 1		−0.012	−0.003		0.118***	0.131***
		(0.016)	(0.016)		(0.022)	(0.023)
Distance to university (thousands of km)			−5.44***			−9.15***
			(0.21)			(0.32)
Distance to university squared			7.21***			12.17***
			(0.36)			(0.53)
Program is in student's region (*Land*)			0.004			0.002
			(0.026)			(0.038)
Program's ranking of student (between zero and one)			0.130			0.448**
			(0.155)			(0.224)
Chances of not receiving an offer from program in Phase 2			−0.018			0.019
			(0.056)			(0.074)
Program fixed effects (376 programs)	Yes	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263	66,263
B. Marginal effects on probability of ranking feasible program as top choice						
Baseline (no early offer) acceptance probability: 38.5%						
Nonfirst early offer (percentage points)				9.7	8.3	8.3
				(1.5)	(1.3)	(1.5)
First early offer (percentage points)					10.8	11.1
					(1.6)	(1.9)
C. Marginal effects on utility (measured in distance)						
Average distance to ranked programs: 126 km						
Nonfirst early offer (km)						−60
First early offer (km)						−76

Notes: This table reports estimates from a rank-ordered logit model for the probability of observing a student's initial and final ROLs of feasible programs. The sample and variables are the same as in Table 3. Columns 1–3 consider students' initial ROLs, while columns 4–6 consider their final ROLs. We take as a student's initial ROL the partial order of feasible programs that she ranked at the beginning of Phase 1. In the analysis of final ROLs, we use only the payoff-relevant information contained in each ROL. In Panel B, for the marginal effect of a nonfirst early offer on the probability of top ranking a program, we measure the difference between the following two predictions on top-ranking behavior: while keeping all other variables at their original values, we let (i) *EarlyOffer* = 1 and *FirstEarlyOffer* = 0 and (ii) *EarlyOffer* = *FirstEarlyOffer* = 0. The baseline probability is the average of the second prediction across students, while the reported marginal effect is the average of the difference between the two predictions across students. The marginal effect of the first early offer is calculated in a similar manner. In Panel C, the marginal effects on utility are computed in the same way as in Table 3. Standard errors are shown in parentheses. **: p <0.05; ***: p <0.01.

First, we consider a more restrictive definition of program feasibility to account for the possibility that students who barely cleared a program's admission cutoff in Phase 2 may have considered this program infeasible ex ante. We relabel as infeasible any program j in student i's initial ROL such that the ratio $r_{i,j}$ between the student's rank under the program's most favorable quota and the rank of the last student who received an offer from the program under that quota is between a prespecified value $\overline{r}$ (< 1) and 1.[25] The sample selection and the dummy for offer acceptance are adjusted according to the new feasibility. Appendix Table B2 summarizes the results from the conditional logit model when we vary the ratio $\overline{r}$ between 0.5 and 1. The early-offer and first-early-offer effects are very similar to the baseline estimates across the values of $\overline{r}$. We also assess and confirm the robustness of our estimates to artificially expanding students' feasible sets (see Appendix Table B3).

Second, we consider the possibly heterogeneous effect of early offers during the first two weeks of Phase 1, since there is some evidence that the very early offers are from slightly less selective programs. Appendix Table B4 shows that our main results are not driven by these very early offers.

How a student ranks her feasible programs in the initial ROL may reflect her preferences. In the investigation of the early-offer effect on offer acceptance, we further control for how the student ranks each program. Appendix Table B5 reveals that this further control does not change our results.

In the analysis of student ranking behavior, one may be concerned that some students' initial ROLs may not be meaningful because students know that they have until the end of Phase 1 to change them. In Appendix Table B6, we restrict the sample to students with an initial ROL that they had reranked at some point in the Application Phase. For a student in this subsample, her initial ROL is more likely to reflect her initial preferences. The results in the table are very similar to those based on the full sample.

Finally, as additional evidence for our main findings, we implement an alternative empirical design to estimate the early-offer effect. We take advantage of the discontinuity around the cutoff rank that allows students to receive an offer in Phase 1 (i.e., an early offer) rather than in Phase 2 and compare the probability that a (potential) offer is accepted by students on either side of the cutoff. While intuitively appealing, this regression

[25] Note that this ratio is the same as the one we use to proxy a student's chances of not receiving an offer from the program in Phase 2 (Table 3, column 5).

discontinuity (RD) design has several limitations in our setting, leading to our decision to not use it as our main empirical strategy.[26] Bearing in mind these limitations, we apply a fuzzy RD design to estimate the impact of receiving a (potential) early offer from a program on the acceptance probability of students who were ranked just above versus just below the program's Phase 1 cutoff rank (see Appendix C for details). Reassuringly, the results are very similar to those from the conditional logit model. The RD estimates indicate that receiving an early offer from a program increases the probability of accepting that program by 8–9 percentage points (see Appendix Table C1).

3 Explanations of the Early-Offer Effect

In this section, we begin by testing and ruling out several possible explanations of the early-offer effect. Our preferred explanation is that students learn about their preferences over programs in the course of the procedure, which is corroborated in a student survey presented at the end of this section. Based on these findings, we develop a model with preference discovery in Section 4 that can explain the early-offer effect.

3.1 Alternative Explanations

Here we discuss alternative explanations of the early-offer effect.

Preference for being ranked high by a program. A student may respond positively to an early offer if she thinks that a program is revealing its appreciation or a high match quality by making her an early offer.[27] This implies that students care about how a program ranks them. If the early-offer effect is driven by students' preferences for being ranked high by a program, the effect would disappear or decrease when we control for how

[26]We identify three limitations of the RD design in our setting. First, in the context of the DoSV procedure, the RD design is fuzzy rather than sharp because students are ranked under multiple quotas for any given program (the average program has six quotas). Namely, a student who fails to clear the Phase 1 cutoff under a program's quota q can receive an early offer from the same program under a different quota q', thus reducing the discontinuity in the early-offer probability at the Phase 1 cutoff under quota q. Second, it allows us to estimate only the early-offer effect on offer acceptance and not to compare the effects of the first versus subsequent early offers or to analyze students' reranking behavior. Third, it identifies the early-offer effect only for the subgroup of students who barely cleared or barely missed the Phase 1 cutoff, whereas we are interested in estimating this effect for a broader population of applicants.

[27]Relatedly, Antler (2019) studies a model in which workers experience a disutility when they are ranked low on the employer's preference list.

a program ranks a student (which is observable to her in the DoSV). With this additional control, column 4 of Table 3 shows that the early-offer effect remains the same.[28]

Immediate reaction. The early-offer effect can be driven by an immediate reaction—for example, from a feeling of relief.[29] However, we find some counterevidence. First, a nonfirst early offer is also more likely to be accepted than nonearly offers (Table 3). Second, students do not immediately accept an offer upon its arrival. The average waiting time before accepting an offer is 9 days (Figure B2 and Table B7 in Appendix B), and the distributions of offers and acceptances on each day of the week differ markedly (Figure B3), with a significant fraction of acceptances occurring on the weekend when almost no offers are made.

Pessimism about future offers. Students may accept early offers if they assign a close to zero probability of receiving a better offer later. However, given the information provided by the DoSV, it is likely that students have a reasonably accurate assessment of the offer probabilities. Taking a student's initial ROL as a proxy of her preferences, we find evidence that the probability of receiving a better offer in Phase 2 is substantial. Among the students who have at least one (potential) offer in Phase 2,[30] almost half rank a Phase 2 offer above *all* early offers in their initial ROLs. These students could have received better offers in Phase 2 had they remained in the system. Moreover, among all students in our sample, 65% have at least one potential offer in either phase that is ranked above their first early offer in their initial ROLs. Therefore, given the information available and the actual possibility of receiving better offers in the future, it seems unlikely that the early-offer effect would be driven by students' pessimistic beliefs.[31]

[28] Appendix Table B8 further shows that our results are robust to controlling for potential nonlinearities in the relationship between a student's rank and her acceptance probability (e.g., students dislike being at the bottom of their class). We perform this test either by including a second-/fourth-order polynomial of a student's rank (between zero and one) or by splitting each program's ranking of applicants into quartiles/deciles and including these indicators as controls. Our estimates remain essentially unchanged.

[29] Theories of dual selves posit that decisions are influenced by an intuitive system, System 1, that performs automated or emotion-driven choices and a deliberative system, System 2, responsible for more reflective decisions. See, e.g., Kahneman (2003, 2011), Loewenstein and O'Donoghue (2004), Fudenberg and Levine (2006), and Evans (2008).

[30] Those who do not have a (potential) Phase 2 offer do not contribute to identifying the early-offer effect, although they do contribute to identifying the first-early-offer effect if they have multiple early offers.

[31] Consistent with this interpretation, our earlier results show that the early-offer and first-early-offer effects are robust to adopting a more restrictive definition of program feasibility (see Appendix Table B2, which excludes programs that students may not have considered as feasible).

Head start in the housing market. Student dormitories are scarce in Germany and can accommodate only a small fraction of students. Hence, a student may accept an offer early to have a head start when searching for housing. However, this incentive does not exist for students who attend a university in their own municipality and often live with their parents. We can therefore test this housing demand hypothesis by checking whether the early-offer effect is also observed in the subsample of students who applied only to local programs. The results are summarized in Appendix Table B9. Despite the relatively small size of this subsample (11.3% of the full sample), the early-offer and first-early-offer effects are statistically significant and similar in magnitude to our baseline estimates.[32] We thus conclude that housing concerns are unlikely to explain the early-offer effect.

Aversion to the computerized assignment. Some students may dislike being assigned by a computerized algorithm in Phase 2 and may therefore actively accept an offer in Phase 1. We document two pieces of evidence to show that this is unlikely to drive our findings. First, almost half of the students actively choose to participate in a computerized assignment in Phase 2 by top ranking an early offer when entering Phase 2 (see Figure 3). Second, the effect of the first early offer is larger than that of other early offers, which cannot be explained by an aversion to the computerized assignment.

Beyond the possible explanations discussed so far, we cannot rule out that early offers create an endowment effect that might cause students to value programs with early offers more than other programs (Kahneman, Knetsch and Thaler, 1990). Our model in Section 4 shows that such a behavioral factor is not necessary to explain the early-offer effect. Moreover, we have direct evidence for our model from a survey. It is presented below and documents that students learn about programs in the course of the DoSV procedure.

[32] As additional evidence, we show in Appendix Table B10 that our results are robust to restricting the sample to students who did not accept an early offer until at least halfway through Phase 1 (i.e., August 2) and hence who are less likely to have accepted an early offer in order to start looking for housing as soon as possible. The estimated early-offer effects are comparable to those using the full sample, while the first-early-offer effects are only slightly smaller when expressed in terms of marginal effect on acceptance probability.

3.2 Evidence from a Survey

To obtain direct information on students' decision-making, we conducted a survey. It was administered by the *Stiftung für Hochschulzulassung* as part of an official survey that was accessible through a link on the website of the DoSV. Around 9,000 students completed it in 2015 (i.e., our sample period). Information about the setup of the survey and the complete list of questions are provided in Appendix A.2.

Table 5 – Evidence from a Survey on Students in the DoSV for 2015–16

	Number of valid answers (1)	Agree/Yes (%) (2)
A. Applied to more than one program ($N = 4,994$)		
At the time of application, I did not have a clear ranking because I still needed to collect information in order to rank my applications according to my preferences[a]	4,573	30
Getting to a ranking was very difficult, and I wanted to postpone this decision for as long as possible[a]	4,555	25
Received at least one offer	4,775	84
B. Applied to more than one program and received at least one offer ($N = 3,999$)		
When comparing the universities that have made you an offer with universities that have not, can it then be said that:		
(a) On average, I spend more time collecting information on the universities that have made me an offer[a]	3,251	61
(b) On average, I spend the same amount of time collecting information on the universities that have made me an offer[a]	3,251	29
(c) On average, I spend less time collecting information on the universities that have made me an offer[a]	3,251	10
Did your ranking change between the beginning of the procedure on July 15 and now?	3,552	30
C. Applied to more than one program, received at least one offer, and reranked programs ($N = 1,072$)		
I have received some early offers that have changed my perception of the universities[a]	1,020	30

Notes: This table is based on the data from an online survey that was conducted between July 27 and October 10, 2015. The different panels correspond to different subgroups of respondents. Column 1 indicates the number of valid answers for each question, i.e., the number of participants who did not choose the option "I do not want to answer this question." Among those who answered the question, column 2 reports either the fraction of participants who responded Yes (if the question requires a dichotomous Yes/No answer), or the fraction who responded that they agree or strongly agree with the statement (if the question uses a five-point Likert scale).
[a] These survey questions are originally based on a five-point Likert scale..

Table 5 considers three different groups of survey respondents in panels A–C. Respondents in Panel A are those who applied to more than one program, accounting for 66% of all respondents. Among them, 30% report that they did not have a clear ranking over programs at the time of application because they needed more research to form their preferences; 25% agree that coming up with a preference ranking was very difficult and that they wanted to delay the decision for as long as possible.

Among respondents who applied to more than one program, 84% had received at least one offer at the time of the survey, including offers from programs not in the DoSV. Panel B shows that receiving an offer increased the time spent on learning about that university for 61% of students, while only 10% spent less time.

Finally, among respondents who applied to more than one program and received at least one offer, 30% modified their ROL at some point between July 15 (the end of the Application Phase) and the time they completed the survey (half of them completed it before August 20). Among these students (Panel C), 30% agreed that their perception of the universities was influenced by the early offers they received.

In sum, the survey results indicate that at the start of the procedure, many students have not yet formed preferences over the programs. Moreover, students tend to invest more time learning about universities from which they receive an offer than about others, and early offers influence their perceptions of the programs.

4 A University Admissions Model with Preference Discovery

Here we develop a model of university admissions. Consistent with the findings from the survey in Section 3.2, it allows students' preference discovery through costly learning about programs. The sequential arrival of early offers under a multioffer mechanism such as the DoSV influences a student's learning behavior and leads to the documented early-offer effect. Further, we compare the DoSV with the canonical single-offer DA and a new mechanism—BM-DA—that improves on the DoSV. Recall that students apply to university programs and that each program admits students.

4.1 The Mechanisms

We start by formally defining the mechanisms. A *multioffer* DA (M-DA) mechanism, of which the DoSV is an example, is defined by the following stages:

Stage 1 (Applications): Through a clearinghouse, students apply to a set of programs without committing to an ROL of these programs.

Stage 2 (Ranking applicants): Every program ranks the students who have applied to it and submits the ranking to the clearinghouse.

Stage 3 (Multioffer stage with continuous offers and rejections): Through the clearinghouse, each program extends admission offers to its top-ranked applicants up to its capacity. Students can reject any offers that they have received. Whenever a program's offer is rejected by a student, the clearinghouse automatically makes a new offer to the top-ranked applicant among those who have not yet received its offer.

Stage 4 (Final ROLs): On a prespecified date, every student commits to an ROL of the programs that she has applied to (and has not rejected offers from).

Stage 5 (Final match): With the rankings from students and programs as well as the remaining seats at each program, the clearinghouse runs the program-proposing GS algorithm and finalizes the matching.

In contrast to the M-DA, the *program-proposing DA mechanism* asks students to commit to an ROL of programs in stage 1 and proceeds to stages 2 and 5, while skipping all others. Note that we distinguish between "mechanism" and "algorithm," although the literature often uses the two terms interchangeably. The GS *algorithm* is a set of computer codes that calculate a matching from information on students and programs, while a mechanism in our setting includes an algorithm and how relevant information is collected from students and programs (Appendix D.1).

A potential concern about the M-DA mechanism is that the sequential arrival of offers may lead to students accepting suboptimal offers. We thus propose the *batched multioffer* DA (BM-DA) mechanism that has a common date for every program to send out its early offers. Specifically, it replaces stage 3 of the M-DA with stage 3', while keeping everything else the same:

Stage 3' (Multioffer stage with offers batched on a common date): On a pre-specified date, every program extends admission offers through the clearinghouse to its top-ranked applicants up to its capacity. Students can reject any offers that they have received.[33]

To summarize, we distinguish between mechanisms under which a student can hold multiple offers for some time and those under which she receives at most one single offer. Accordingly, the DA is a single-offer mechanism, while the M-DA and the BM-DA allow multiple offers, with a more structured offer arrival under the BM-DA. Note that the multioffer mechanisms rely on the program-proposing GS algorithm instead of the

[33] In some cases, it can be helpful to have multiple rounds of offers. We provide a discussion in Section 5.

student-proposing version. The latter cannot be used in a multioffer mechanism because the student-proposing GS algorithm allows each program only to *tentatively* accept a student before the algorithm concludes and thus does not generate offers until the very end.

4.2 Model Setup and Welfare Comparison

In the model, there is a student in a finite time horizon of $J + 2$ ($J \geqslant 2$) periods, $t \in \{0, 1, \ldots, J, J + 1\}$.[34] We focus on two time points in each period, the beginning and the end, implying that actions can be taken by the student during a period. There is no time discounting.

At the beginning of period 0, the student has applied to a set of programs, $\mathcal{J}$ ($|\mathcal{J}| = J$). In period 0, the student has the belief that she will receive an offer from $j \in \mathcal{J}$ in period $J + 1$ with probability $p_j^0 \in (0, 1)$. Let $p^0 \equiv (p_1^0, \ldots, p_J^0)$. As we shall clarify shortly, the student does not update her belief about offer probabilities unless she receives an offer before period $J + 1$. Admission decisions are independent across programs.

Program j's quality is a random variable, X_j, whose distribution function is G_j. Random variables X_j and $X_{j'}$ are independent for any $j \neq j'$. Let $G = \prod_j G_j$ represent the joint distribution.

The student's valuation of program j is $u(X_j)$, where $u(X_j)$ is weakly concave, implying that she can be risk neutral or risk averse. She has access to an outside option that can be an admission offer from another program outside of the system. This outside option gives her zero utility and is forfeited if she accepts an offer from any $j \in \mathcal{J}$.

At the beginning of period 0, the student knows only the distribution of X_j, G_j. She can pay a cost, c, to learn a program's (realized) quality and thus discover her preferences. As we shall specify below, the student's preference discovery is sequential. That is, she decides which program to learn about first and whether to learn about another program (conditional on what has been learned), and so on and so forth.

Remark 1. *Our model deviates from the common assumption in the matching literature that agents know their own ordinal preferences (Roth and Sotomayor, 1990; Bogomolnaia*

[34]Unlike the matching literature, we study a single-agent model to highlight the learning dynamics in preference discovery. The comparison among the mechanisms therefore ignores equilibrium effects that other students' behavior may cause. Our simulations in Section 4.4 provide some idea about the magnitude of these equilibrium effects and reveal that the results from the single-agent problem still hold.

and Moulin, 2001). Under this assumption, Appendix D.2 shows that the early-offer effect documented in Section 2 cannot emerge. Intuitively, conditional on a student's applications, $\mathcal{J}$, knowing her own ordinal preferences is sufficient for her to make an optimal decision.

Periods 1 to J constitute the multioffer stage in the M-DA and BM-DA mechanisms. During this stage, there can be at most one *early offer* arriving at the beginning of each period. No offer can be rescinded. Let $O = (O_1, \ldots, O_J) \in \{1, \ldots, J, J+1\}^J$ be an *offer arrival* such that $O_j = t$ for $1 \leqslant t \leqslant J$ if the student receives an offer from program j in period t and that $O_j = J + 1$ if she *does not* receive an offer from program j before period $J + 1$. Note that $O_j = J + 1$ *does not* imply that she will necessarily receive an offer from j in period $J + 1$. There is no early offer in period 0.

Timeline under the DA: The student is required to rank the J programs at the end of period 0 before any possible early offers. Therefore, her preference discovery activities, if any, take place in period 0.

Timeline under the BM-DA: The student must rank the J programs at the end of period J. At the beginning of period J, she observes all early offers given O. The offer probabilities are updated from p^0 to $p^J(O)$ such that (i) $p_j^J(O) = p_j^0$ if $O_j = J + 1$ and (ii) $p_j^J(O) = 1$ if $O_j < J + 1$. She makes a decision on preference discovery given $p^J(O)$.

Timeline under the M-DA: The student must submit an ROL of the J programs at the end of period J, but her learning decision is made "myopically" period by period as follows. Define $\underline{t} = \min\{\min\{O\}, J\}$, such that $\underline{t}$ represents the period when her first early offer arrives, if any, or period J if there is no early offer. The student does not learn anything in period t for all $t < \underline{t}$. At the beginning of period t, for $\underline{t} \leqslant t \leqslant J$, the student updates her offer probabilities according to offer arrival O from $p^{(t-1)}(O)$ to $p^t(O) = (p_1^t(O), \ldots, p_J^t(O))$, such that (i) $p_j^t(O) = p_j^0$ if $O_j > t$ (i.e., no offer from j up to period t), and (ii) $p_j^t(O) = 1$ if $O_j \leqslant t$ (i.e., an offer from j arrives in period t or earlier). Conditional on $p^t(O)$ and what the student has learned up to period $(t-1)$, she decides whether to learn more, assuming (incorrectly) that there will be no more offers before period $(J+1)$. If $\min\{O\} = J + 1$ (i.e., there is no early offer at all), she makes a decision on preference discovery in period J given that $p^J(O) = p^0$.

We assume that under the M-DA the student ignores the possibility of receiving more early offers in later periods. In practice, some students under the M-DA behave in this manner, as we have seen in our data. If all students are fully rational, they would not make a learning decision until all early offers have been received, making the DoSV (an application of the M-DA) equivalent to the BM-DA (conditional on offer arrival). In this case, there would be no difference between the first and later early offers, provided that offers arrive randomly. However, Section 2.3 shows that the first early offer has a larger effect than later early offers.

Remark 2. *As shown below, depending on the mechanism in place, the student endogenously discovers her preferences over the programs. Given her information set at the time of ROL finalization, each mechanism has the same properties as the program-proposing DA: it is stable with respect to reported ordinal preferences and not strategy-proof for students or programs.*[35]

4.2.1 Learning Strategy in a Given Period

We now consider the student's learning strategy in a given period with up-to-date offer probabilities $p \in (0,1]^J$. This is precisely what she does under the DA or BM-DA, because preference discovery happens only in one period. We will extend the derivation to discovery in multiple periods under the M-DA.

Let $\mathcal{U} \subseteq \mathcal{J}$ be the set of programs whose qualities have not yet been learned by the student, and let $\overline{\mathcal{U}} = \mathcal{J} \backslash \mathcal{U}$. Also let $l(\overline{\mathcal{U}}) = \{(j, x_j)_{j \in \overline{\mathcal{U}}}\} \in (\mathcal{J} \times \mathbb{R})^{|\overline{\mathcal{U}}|}$ be the realized program qualities already learned by the student, paired with their identities.

Given a state $(\mathcal{U},\, l)$ and offer probabilities p, the student's learning strategy is given by $\psi(\mathcal{U}, l \mid p) \in \{0\} \cup \mathcal{U}$, such that $\psi = 0$ when the student stops learning and $\psi \in \mathcal{U}$ indicates which program to learn next. With this definition, we consider only pure strategies.[36]

Given $(\mathcal{U},\, l,\, p)$, if $\psi = 0$, the student then submits an ROL. The expected utility from an ROL is calculated as follows. For $j \in \overline{\mathcal{U}}$, define $v_j = \max\{0, u(x_j)\}$, in which x_j is the realized value of X_j; for $j \in \mathcal{U}$, $v_j = \max\{0, \int u(x) dG_j(x)\}$. Recall that the outside option yields zero utility. Given her information, it is optimal for the student to submit a truthful ROL of all acceptable programs (i.e., $v_j > 0$).[37] Not taking into

[35] Under the assumption that student preferences evolve over time exogenously, Narita (2018) investigates the properties of alternative mechanisms.

[36] A mixed strategy implies that in some state, the student is indifferent between two different actions. This may happen for a measure zero set of $(\mathcal{U}, l)$ when G_j admits a continuous density function for all j.

[37] We assume that including a program in a submitted ROL is a commitment to accepting the program's offer if it is the highest-ranked offer. Equivalently, we may assume that there is a cost to reject an unacceptable offer that is included in the student's ROL.

account the learning costs that are already sunk, the expected utility from this ROL is $v(\mathcal{U}, l, p) = p_{j_1} v_{j_1} + \sum_{k=2}^{J} p_{j_k} v_{j_k} \prod_{k'=1}^{k-1} (1 - p_{j_{k'}})$, where $v_{j_k} \geqslant v_{j_{k'}}$ whenever $k < k'$.

If the student adopts strategy ψ, her expected utility given ($\mathcal{U}$, l, p) is given by

$$
\begin{aligned}
V(\mathcal{U}, l, p \mid \psi) =& \mathbb{1}_{(\psi(\mathcal{U}, l|p)=0)} \times v(\mathcal{U}, l, p) \\
&+ \sum_{j \in \mathcal{U}} \mathbb{1}_{(\psi(\mathcal{U}, l|p)=j)} \left(\int V(\mathcal{U} \backslash \{j\}, l \cup \{(j, x_j)\}, p \mid \psi) dG_j(x_j) - c \right),
\end{aligned}
$$

where $\mathbb{1}_{(\cdot)}$ is an indicator function. Thus, $V(\mathcal{J}, \varnothing, p \mid \psi)$ is the student's expected payoff from adopting strategy ψ before she starts discovering her preferences.

An optimal strategy, ψ^*, solves the following problem for every state $(\mathcal{U}, l)$ given p:

$$
V(\mathcal{U}, l, p \mid \psi^*) = \max \left\{ v(\mathcal{U}, l, p), \max_{j \in \mathcal{U}} \left\{ \int V(\mathcal{U} \backslash \{j\}, l \cup \{(j, x_j)\}, p \mid \psi^*) dG_j(x_j) - c \right\} \right\}.
$$

In other words, $\psi^*(\mathcal{U}, l \mid p) = 0$ if $v(\mathcal{U}, l, p) \geqslant \int V(\mathcal{U} \backslash \{j\}, l \cup \{(j, x_j)\}, p | \psi^*) dG_j(x_j) - c$ for all $j \in \mathcal{U}$; otherwise, $\psi^*(\mathcal{U}, l \mid p) = \arg\max_{j \in \mathcal{U}} \{ \int V(\mathcal{U} \backslash \{j\}, l \cup \{(j, x_j)\}, p \mid \psi^*) dG_j(x_j) \}$. By definition, $V(\mathcal{J}, \varnothing, p \mid \psi^*) \geqslant V(\mathcal{J}, \varnothing, p \mid \psi)$ for all ψ.

Preference discovery under the DA: The student discovers her preferences over the programs in period 0. That is, she starts learning given $(\mathcal{J}, \varnothing, p^0)$. Let $\psi^{DA}(\cdot, \cdot \mid p^0)$ represent an optimal strategy.

Preference discovery under the BM-DA: The student learns about her preferences in period J after receiving all early offers as prescribed by offer arrival O. Hence, she starts learning given $(\mathcal{J}, \varnothing, p^J(O))$. Let $\psi^B(\cdot, \cdot \mid p^J(O))$ represent an optimal strategy.

4.2.2 Preference Discovery under the M-DA

We now extend the analysis to the M-DA under which the student's preference discovery can be updated upon the arrival of an early offer. Recall that $\underline{t} = \min\{\min\{O\}, J\}$. In each period $t = \underline{t}, \ldots, J$, given $p^t(O)$, the student has a myopic strategy, $\psi^t(\cdot, \cdot \mid p^t(O))$, leading to (subjective) expected utility $V^t(\mathcal{U}^{(t-1)}, l^{(t-1)}, p^t(O) \mid \psi^t(\cdot, \cdot \mid p^t(O)))$, where $\mathcal{U}^{(t-1)}$ and $l^{(t-1)}$ represent the learning outcomes at the end of period $(t-1)$ and $\mathcal{U}^{(\underline{t}-1)} = \mathcal{J}$ and $l^{(\underline{t}-1)} = \varnothing$. Hence, $\psi^t \in \arg\max_{\psi} V^t(\mathcal{U}^{(t-1)}, l^{(t-1)}, p^t(O) \mid \psi)$, for $t = \underline{t}, \ldots, J$.

The M-DA thus leads to a sequence of learning strategies, $\{\psi^t\}_{t=\underline{t}}^J$. Importantly, the learning technology is such that the student cannot "un-learn" what has been learned. We show in Appendix D.4 that under an assumption of no learning on off-equilibrium paths

(Assumption D1), for any state, there is at most one strategy in the sequence $\{\psi^t\}_{t=\underline{t}}^J$ requiring the student to learn more (Lemma D1). Therefore, we can define $\psi^M(\mathcal{U}, l \mid p^J(O)) = \max_{t\in\{\underline{t},\ldots,J\}} \psi^t(\mathcal{U}, l \mid p^t(O))$ for all $(\mathcal{U}, l)$. Under Lemma D1, $\psi^M(\mathcal{U}, l \mid p^J(O))$ is equivalent to applying $\{\psi^t\}_{t=\underline{t}}^J$ sequentially.

4.2.3 Welfare Dominance of the BM-DA over the DA and M-DA

For each mechanism, we study the student's welfare at the beginning of period 0 (i.e., before any preference discovery) conditional on offer arrival O. Thus, we do not need to specify a distribution for O.

Under the DA, the expected utility at the beginning of period 0 is evaluated at $p^J(O)$, resulting in $V(\mathcal{J}, \varnothing, p^J(O) \mid \psi^{DA}(\cdot,\cdot \mid p^0))$. Notice that the learning strategy is determined based on p^0 without knowing the offer arrival O, which is a source of inefficiency. Under the M-DA, it is $V(\mathcal{J}, \varnothing, p^J(O) \mid \psi^M(\cdot,\cdot \mid p^J(O)))$, and under the BM-DA it is $V(\mathcal{J}, \varnothing, p^J(O) \mid \psi^B(\cdot,\cdot \mid p^J(O)))$. We then have the following result.

Proposition 1. *Conditional on the offer arrival O, in terms of the student's expected utility at the beginning of period* 0*,*

(i) the BM-DA mechanism dominates both the M-DA and the DA mechanisms:

$$V\left(\mathcal{J}, \varnothing, p^J(O) \mid \psi^B(\cdot,\cdot \mid p^J(O))\right) \geqslant V\left(\mathcal{J}, \varnothing, p^J(O) \mid \psi^M(\cdot,\cdot \mid p^J(O))\right),$$
$$V\left(\mathcal{J}, \varnothing, p^J(O) \mid \psi^B(\cdot,\cdot \mid p^J(O))\right) \geqslant V\left(\mathcal{J}, \varnothing, p^J(O) \mid \psi^{DA}(\cdot,\cdot \mid p^0)\right),$$

with each inequality being strict for some $(\mathcal{J}, p^0, O, F, c)$; and

(ii) the welfare ranking between the M-DA and the DA is ambiguous.

For an arbitrary distribution of O, part (i) still holds in terms of the student's unconditional expected utility in period 0 because it is satisfied for all possible O.

4.3 Costly Preference Discovery and Early-offer Effect: A Numerical Example

Our empirical analysis documents that an early offer increases the probability that the offer is accepted and that the effect is larger for the first offer. We now present a numerical example to highlight how these effects can be caused by the student's learning about program qualities.[38] Moreover, we clarify a disadvantage of the M-DA: if a low-quality program makes an offer first, this may suboptimally increase the probability that the student will accept its offer. We show that this inefficiency is avoided by the BM-DA.

The student is risk neutral, $u(X) = X$. There are two programs, $\mathcal{J} = \{1, 2\}$. The quality of program j is an independent draw from $Uniform(\mu_j - 0.5, \mu_j + 0.5)$, with $\mu_1 = 1/16$ and $\mu_2 = 1/32$. As seen in period $t = 0$, the probability of receiving an offer in period $t = J + 1$ from program 1 is $p_1^0 = 9/16$ and that from program 2 is $p_2^0 = 9/16$. The cost of learning a program's quality is $c = 1/20$. Everything else is the same as in Section 4.2. For instance, there is an outside option whose value is zero.

There are five different types of offer arrivals, $O^{\varnothing}$ (no early offer), $O^{\{1\}}$ (an early offer from program 1), $O^{\{2\}}$ (an early offer from program 2), $O^{\{1,2\}}$ (early offers from program 1 and then program 2), and $O^{\{2,1\}}$ (early offers from program 2 and then program 1). Below, we investigate optimal learning (Section 4.3.1), ranking behavior (Section 4.3.2), and the efficiency of the mechanisms (Section 4.3.3).

4.3.1 Learning Behavior

The student's learning strategy under a given mechanism has two parts: which program to learn first and, depending on what has been learned, whether to learn about the other program. We solve her optimization problem by backward induction.

Suppose that the offer arrival is $O^{\varnothing}$ (no early offer). If the student first learns X_1, the decision of whether to learn X_2 is depicted in Panel A of Figure 5. When the realization of X_1, x_1, is below the threshold (the dashed vertical line on the right), $X_1^*(p_1^0, p_2^0) = \mu_2 + \frac{1}{2} - \sqrt{\frac{2c-(1-p_1^0)p_2^0(\mu_2-\frac{1}{2})}{p_1^0 p_2^0}} \approxeq 0.150$, the student learns X_2; otherwise, she stops learning. Intuitively, with a higher value of x_1, the incentive to learn X_2 is lower because she can stop learning and top rank program 1 to guarantee herself an expected payoff of $p_1^0 x_1 + (1 - p_1^0)p_2^0\mu_2$. Similar thresholds can be derived when the student learns X_2 first and/or when there are one or two early offers (for detailed derivations, see Grenet, He and Kübler, 2021).

We now consider which program to learn first. For $j, j' \in \{1, 2\}$, let X_j*–then–*$X_{j'}$ denote

[38] A working paper version of this article, Grenet, He and Kübler (2021), considers a more general setting. It implies that the numerical example here is not a knife-edge case. We also note that the positive early-offer effect on offer acceptance does not always emerge. Appendix D.3 provides an example in which an early offer from a program *reduces* the likelihood that the offer is accepted. Besides, there is no first-early-offer effect. The main feature of that example is that the student never has any incentive to learn about one of the two programs.

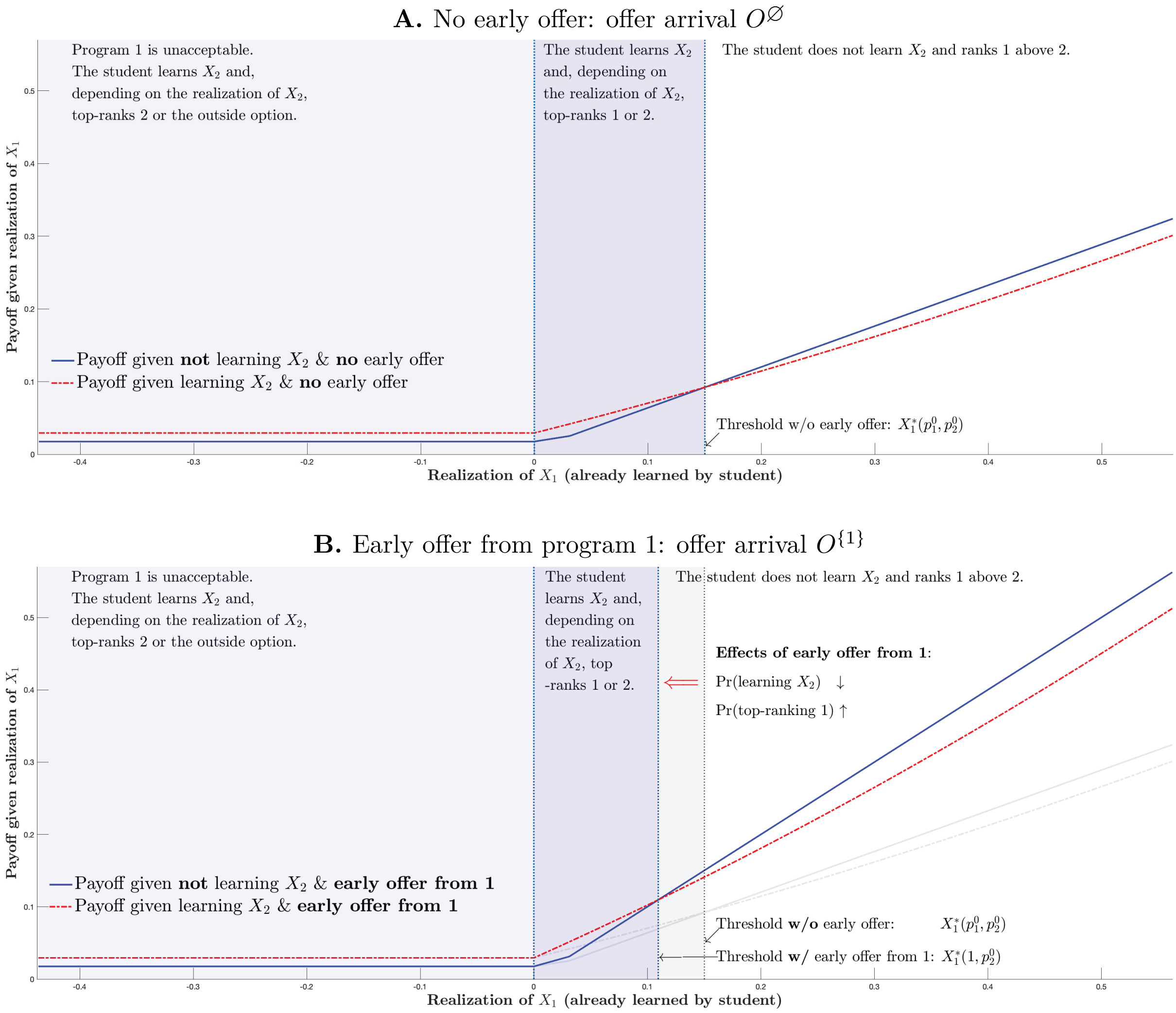


Figure 5 – Learning and Ranking Behaviors with or without an Early Offer from Program 1

Notes: This figure applies to both the M-DA and the BM-DA. We set $\mu_1 = 1/16$, $\mu_2 = 1/32$, $p_1^0 = 9/16$, $p_2^0 = 9/16$, and $c = 1/20$. In Panel A, the student receives no early offer. She learns X_1 first and continues to learn X_2 if and only if the realization of X_1, x_1, is below $X_1^*(p_1^0, p_2^0) = \mu_2 + 1/2 - ((2c - (1-p_1^0)p_2^0(\mu_2 - 1/2)^2)/p_1^0 p_2^0)^{1/2}$. If $x_1 \in [X_1^*(p_1^0, p_2^0), \mu_1 + 1/2]$, the student submits ROL 1–2. If $x_1 \in [0, X_1^*(p_1^0, p_2^0))$, she will learn X_2 and submits a truthful ROL among 1–2, 2–1, and 1–0. If $x_1 \in [\mu_1 - (1/2), 0)$, she will learn X_2 and submits a truthful ROL, either 2–0 or 0–0 (an empty ROL). In Panel B, the student receives an early offer from program 1, and it is still optimal to learn X_1 first. The probability of learning X_2 decreases because the threshold drops from $X_1^*(p_1^0, p_2^0)$ to $X_1^*(1, p_2^0) = \mu_2 + 1/2 - (2c/p_2^0)^{1/2}$. The probability of top ranking program 1 increases: for $x_1 \in [X_1^*(1, p_2^0), X_1^*(p_1^0, p_2^0)]$, she now always submits ROL 1–2 instead of one of the ROLs 1–2, 2–1, and 1–0.

that the student first learns X_j and then, depending on the realization of X_j, possibly learns $X_{j'}$. It involves pairwise welfare comparisons among X_1–then–X_2, X_2–then–X_1, and no learning. Given $O^{\varnothing}$ and the parameter values, we can show that it is optimal to learn X_1 first, as depicted in Panel A of Figure 5.

Result 1. *Suppose that the offer arrival is O. The student's optimal learning sequence is as follows:*

(i) if $O = O^{\varnothing}$, X_1–then–X_2 under the M-DA or the BM-DA;

(ii) *if* $O = O^{\{1\}}$, X_1*–then–*X_2 *under the M-DA or the BM-DA;*

(iii) *if* $O = O^{\{2\}}$, X_2*–then–*X_1 *under the M-DA or the BM-DA;*

(iv) *if* $O = O^{\{1,2\}}$, X_1*–then–*X_2 *under the M-DA or the BM-DA;*

(v) *if* $O = O^{\{2,1\}}$, X_2*–then–*X_1 *under the M-DA, but* X_1*–then–*X_2 *under the BM-DA.*

(vi) *Under the DA, since the student has to carry out preference discovery before receiving any early offer, the optimal sequence is always* X_1*–then–*X_2*.*

Table 6 – Learning, Ranking, and Welfare Given Offer Arrival

Mechanism		$O^{\varnothing}$: No early offer (1)	$O^{\{1\}}$: early offer from program 1 (2)	$O^{\{2\}}$: early offer from program 2 (3)	$O^{\{1,2\}}$: early offers from program 1 and then 2 (4)	$O^{\{2,1\}}$: early offers from program 2 and then 1 (5)
		A. Discovery probabilities (×100)				
DA	Pr(learn X_1)	100	100	100	100	100
	Pr(learn X_2)	58.8	58.8	58.8	58.8	58.8
M-DA	Pr(learn X_1)	100	100	61.0	100	71.5
	Pr(learn X_2)	58.8	54.7	100	65.3	100.0
BM-DA	Pr(learn X_1)	100	100	88.6	100	100
	Pr(learn X_2)	58.8	54.7	100	65.3	65.3
		B. Probabilities of top ranking a program (×100)				
DA	Pr(top rank prog. 1)	49.4	49.4	49.4	49.4	49.4
	Pr(top rank prog. 2)	30.1	30.1	30.1	30.1	30.1
M-DA	Pr(top rank prog. 1)	49.4	51.0	33.3	47.1	37.2
	Pr(top rank prog. 2)	30.1	28.5	46.2	32.4	42.3
BM-DA	Pr(top rank prog. 1)	49.4	51.0	33.3	47.1	47.1
	Pr(top rank prog. 2)	30.1	28.5	46.2	32.4	32.4
		C. Welfare conditional on offer arrival (×1000)				
DA		57.7	122.4	95.1	156.3	156.3
M-DA		57.7	122.6	112.0	157.0	153.9
BM-DA		57.7	122.6	112.0	157.0	157.0

Notes: These results are calculated for $\mu_1 = 1/16$, $\mu_2 = 1/32$, $p_1^0 = 9/16$, $p_2^0 = 9/16$, and $c = 1/20$.

For the M-DA, Result 1 considers the learning sequence in the period when the first offer arrives, provided that $O \neq O^{\varnothing}$. It shows that offer arrival determines the optimal learning sequence. In turn, it affects the probability of a program's quality being learned; when the optimal sequence is X_j–then–$X_{j'}$, X_j is learned for certain while $X_{j'}$ is learned only with some probability. This is illustrated in Panel A of Table 6. In column 1, given $O^{\varnothing}$, the probability of X_1 being learned is one under the M-DA or BM-DA, but it decreases to 61.0% under the M-DA or BM-DA when there is an early offer from program 2 (column 3). This is because the early offer changes the optimal learning sequence.

Even when the optimal sequence remains the same, the learning probability can change for the program that is learned second. In column 2 of Table 6, when the student receives an early offer from program 1 and thus the offer arrival changes from $O^{\varnothing}$ to $O^{\{1\}}$, the probability of X_2 being learned decreases from 58.8% to 54.7% under either the M-DA or the BM-DA. This is depicted in Figure 5: the threshold of X_1, X_1^*, below which the student does not learn X_2 is lower given $O^{\{1\}}$ (Panel B) than given $O^{\varnothing}$ (Panel A).

4.3.2 Ranking Behavior under the M-DA

We now explore how early offers affect the student's ROL of the programs. Investigating the student's ranking behavior amounts to studying her offer acceptance because conditional on eventually receiving offers from both programs, the top-ranked program will be accepted by the student. This is similar to our empirical analysis of offer acceptance in which we focus on a student's ex post feasible programs that would make her an offer.

Panel A of Figure 5 shows that given $O^{\varnothing}$ and if $x_1 > X_1^*(p_1^0, p_2^0)$, the student stops learning and submits ROL 1–2. If $0 < x_1 \leqslant X_1^*(p_1^0, p_2^0)$, she learns X_2 and submits a truthful ROL, 1–2, 2–1, or 1–0. If $x_1 < 0$, she learns X_2 and submits a truthful ROL, 2–0 or 0–0 (an empty ROL). However, when the offer arrival becomes $O^{\{1\}}$ (Panel B), for $X_1^*(1, p_2^0) < x_1 < X_1^*(p_1^0, p_2^0)$, the new optimal strategy is to stop learning and submit ROL 1–2, while there is no change for other values of x_1. This increases the probability that program 1 is top ranked, from 49.4% to 51.0% under the M-DA as shown in columns 1 and 2 in Panel B of Table 6. The table provides more examples of this early-offer effect that are summarized in Result 2.

Result 2. *Receiving an offer from one of the programs, either as the first or as the second early offer, strictly increases the probability that this program is top ranked in the student's submitted ROL under the M-DA, ceteris paribus.*

Result 2 describes the effect of receiving an early offer from j, holding everything else constant. For example, it calculates the difference in the probability of program 1 being top ranked between $O^{\{1\}}$ and $O^{\varnothing}$, between $O^{\{1,2\}}$ and $O^{\{2\}}$, or between $O^{\{2,1\}}$ and $O^{\{2\}}$.

When there are two early offers, arrival sequence matters under the M-DA. The following result shows the first-early-offer effect on ranking behavior under the M-DA.

Result 3. *Suppose that there are two early offers. Under the M-DA, the probability of a* *program being top ranked in the student's submitted ROL is higher when its offer is the first one than when it is the second.*

Result 3 focuses on the difference in the probability of program 1 being top ranked between $O^{\{1,2\}}$ and $O^{\{2,1\}}$; a similar comparison is also made for program 2. For example, when we move from column 4 to column 5 in Panel B of Table 6, the early offer from program 2 becomes the first offer, and the probability of program 2 being top ranked increases from 32.4% to 42.3% under the M-DA. Results 2 and 3 are consistent with our empirical findings in Section 2.

4.3.3 Welfare Dominance of the BM-DA and Welfare Loss under the M-DA

We now compare student welfare under the three mechanisms. Given the parameter values, we show that some of the weak inequalities in Proposition 1 are strict. In particular, we highlight that the M-DA can result in a welfare loss when a low-quality offer arrives first.

Result 4. *Suppose that the offer arrival is O. We have the following results on student welfare:*

1. **Dominance of the BM-DA**: *Conditional on O, the BM-DA dominates the DA, and the dominance is strict if $O \neq O^{\varnothing}$ (i.e., there is at least one early offer); the BM-DA also dominates the M-DA, and the dominance is strict when $O = O^{\{2,1\}}$ (i.e., early offers from program 2 and then program 1).*

2. **Comparison between the DA and the M-DA**: *Conditional on O, the M-DA is equivalent to the DA if $O = O^{\varnothing}$; the DA strictly dominates the M-DA if $O = O^{\{2,1\}}$; the M-DA strictly dominates the DA if $O \neq O^{\varnothing}$ and $O \neq O^{\{2,1\}}$.*

Result 4 is illustrated in Panel C of Table 6. Specifically, given $O = O^{\{2,1\}}$ (column 5), the M-DA leads to a welfare loss relative to both the DA and the BM-DA. Under the M-DA, the student's optimal learning sequence is X_2–then–X_1, starting with the ex ante low-quality program (Panel A). As Result 3 shows, the student has a higher probability of top ranking program 2 (Panel B), often without learning X_1. Hence, the student misses some chances of being assigned to program 1. This inefficiency is avoided by the BM-DA under which the optimal learning sequence is X_1–then–X_2.

4.4 Simulation Results

To gauge the relative performance of the DA, M-DA, and BM-DA mechanisms in a real-life setting, we calibrate a set of simulations with the same data used in Section 2. Owing to the data limitations and the lack of a fully fledged empirical model, certain simplifying assumptions are needed in the simulations. We highlight these assumptions below, while the details of the simulation procedure are in Appendix E.

Setup. We construct a stylized market based on the DoSV data. As in Section 2, we use the 21,711 students who applied to at least two feasible programs and accepted an offer. In every simulation, student i always applies to the same set of programs, $\mathcal{A}_i$, including those in her initial ROL and an outside option.[39] A program's capacity is set equal to the number of students in the simulation sample who accepted its offer in reality. Each program ranks its applicants by the average of their *Abitur* percentile rank (between zero and one) and a program-specific *Uniform*$(0,1)$ random variable.

The timeline is as follows: (i) under the DA, students submit their ROL before receiving any offer; (ii) under the M-DA, each program sends out a single batch of early offers at a random time to its highest-ranked applicants up to its capacity and the ROL submission is after the arrival of early offers; (iii) under the BM-DA, the timing is the same as under the M-DA except that all early offers are sent out on the same date. Under any mechanism, the matching is determined by the program-proposing GS algorithm, using as inputs the submitted ROLs and the programs' capacities and rankings of students.

Preference discovery. As in our theoretical model, students are uncertain about their preferences over programs and can learn their quality only at a cost. If student i pays the cost, she discovers her true utility from program j, $U_{i,j}^{\text{FullInfo}}$; otherwise, she values j at $U_{i,j}^{\text{NoInfo}}$. At the time of submitting her ROL, student i's perceived utility from program j under mechanism m is specified as

$$U_{i,j}^{m} = \lambda_{i,j}^{m} \cdot U_{i,j}^{\text{FullInfo}} + (1 - \lambda_{i,j}^{m}) U_{i,j}^{\text{NoInfo}} \quad \forall i, j \in \mathcal{A}_i, \tag{3}$$

[39] This outside option accounts for the possibility that students may have applied to programs outside the DoSV procedure and devoted some time to discovering their quality. Since all students in our sample accepted an offer from the clearinghouse, we make the simplifying assumption that this outside option is never feasible.

where $\lambda^m_{i,j} \in \{0, 1\}$ is an indicator for whether i has learned her true utility from j.

Further, $U^{\text{FullInfo}}_{i,j} = V^{\text{FullInfo}}_{i,j} + \epsilon^{\text{FullInfo}}_{i,j}$, where $V^{\text{FullInfo}}_{i,j}$ depends on observable student-program-specific characteristics and $\epsilon^{\text{FullInfo}}_{i,j}$ is i.i.d. type I extreme value distributed. To calculate $V^{\text{FullInfo}}_{i,j}$, we rely on the same sample as in Section 2.[40] Under the assumption that a student always learns her preference for her first early offer, $V^{\text{FullInfo}}_{i,j}$ is computed by imposing that j is her first early offer. Similarly, we assume that $U^{\text{NoInfo}}_{i,j} = V^{\text{NoInfo}}_{i,j} + \epsilon^{\text{NoInfo}}_{i,j}$, where $V^{\text{NoInfo}}_{i,j}$ is drawn from a normal distribution with mean $V^{\text{FullInfo}}_{i,j}$ and $\epsilon^{\text{NoInfo}}_{i,j}$ is a type I extreme value such that $\epsilon^{\text{NoInfo}}_{i,j} \perp \epsilon^{\text{FullInfo}}_{i,j}$.

Lacking an estimate of learning costs, we assume that under any mechanism, student i discovers her true preferences for half of the programs in $\mathcal{A}_i$. Further deviating from the endogenous discovery in Section 4.2, we impose the following assumptions. Under the DA, the programs whose qualities are learned by i (i.e., $\lambda^{\text{DA}}_{i,j} = 1$) are randomly selected. Under the M-DA, we emulate the myopic learning behavior in Section 4.2 by assuming that i always learns the quality of her first early offer and then alternates between (i) learning the quality of a randomly chosen program from the ones in $\mathcal{A}_i$ that she has not learned yet and (ii) learning the quality of her early offers (if any) in their arrival order. Under the BM-DA, early offers are learned before other programs.

Results. The simulations generate students' submitted ROLs and matching outcomes under the three mechanisms in 10,000 samples. As a benchmark, we also simulate the matching that would have been observed under full information.

Panel A of Figure 6 contrasts the mechanisms by students' preference discovery. The simulations confirm that in terms of discovery, (i) the M-DA and BM-DA mechanisms are both more efficient than the DA and (ii) the BM-DA slightly outperforms the M-DA. On average, across the simulation samples, 44.0% of students rank ex post feasible programs in the order of their full information preferences under the BM-DA, relative to 43.3% and 40.6% under the M-DA and the DA, respectively.[41]

As for student welfare, we compute each student's expected utility as the average utility ($U^{\text{FullInfo}}_{i,j}$) from her matches across the simulation samples. We then perform pairwise

[40] We estimate a rank-ordered logit model that is an augmented version of the specification in column 3 of Table 3, in which we fully interact the early-offer and first-early-offer dummies with university fixed effects, field-of-study fixed effects, distance, distance squared, and a dummy for whether the program is in the student's region. This model is estimated using the information extracted from a student's final ROL.

[41] The comparisons are restricted to ex post feasible programs since it is payoff-irrelevant for a student to rank an infeasible program arbitrarily.

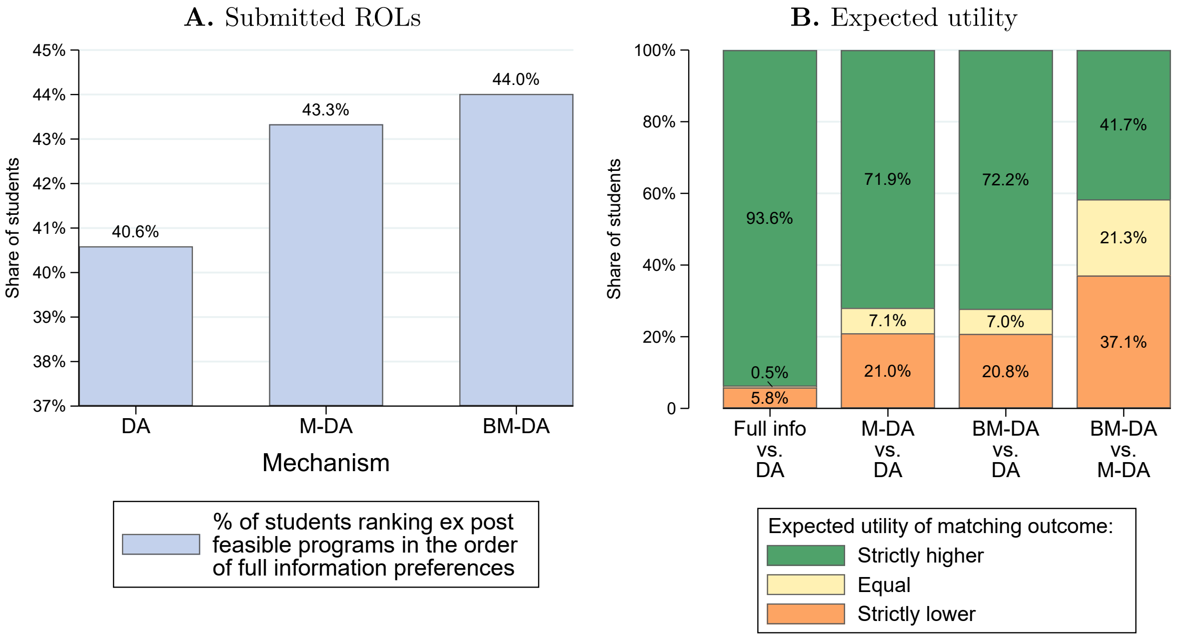


Figure 6 – Comparing the DA, M-DA, and BM-DA Mechanisms: Simulation Results

Notes: Using the simulations detailed in Appendix E, this figure compares the DA, M-DA, and BM-DA mechanisms along two dimensions: students' submitted ROLs (Panel A) and their expected utility of the matching outcome (Panel B). There are 21,711 students. Panel A: Comparison of the share of students who, under each mechanism, rank the ex post feasible programs to which they applied in the order of their full-information preferences, averaged across 10,000 simulation samples. Panel B: Pairwise comparisons of mechanisms based on the shares of students whose expected utility is (i) strictly higher under the first mechanism than under the second, (ii) strictly lower, or (iii) equal. A student's expected utility is the average of the full-information utility of her matches across the 10,000 simulation samples.

comparisons of the mechanisms based on the shares of students whose expected utility is (i) strictly higher under one mechanism than under the other, (ii) strictly lower, or (iii) equal. These comparisons incorporate equilibrium effects since a student's match depends not only on her submitted ROL but also on other students' behavior. As shown in Panel B of Figure 6, the majority of students (over 70%) are strictly better off under the M-DA and the BM-DA than under the DA. Moreover, the BM-DA outperforms the M-DA, as 41.7% of students are strictly better off under the BM-DA than under the M-DA, while only 37.1% are worse off.

Overall, these simulations provide suggestive evidence that the M-DA and the BM-DA can generate sizable welfare gains relative to the DA. Furthermore, the batching of early offers in the BM-DA mechanism is found to yield a small yet meaningful improvement on the M-DA.

5 Concluding Remarks

In recent years, matching markets have become more centralized and increasingly rely on single-offer mechanisms. This trend has been especially prominent in school choice and university admissions where students are required to rank a large number of schools or universities before receiving an offer. Theoretical justifications are usually based on the assumption that agents know their own preferences upon participating in a matching market.

Relying on a unique data set from Germany's university admissions, we identify a quasi experiment in which the arrival time of admission offers is as good as random. We show that a student is more likely to accept an early offer relative to later offers, despite the fact that offers do not expire until the end of the admission procedure. This finding cannot be reconciled with the assumption that students have full information on their own preferences over university programs. Instead, it is consistent with students' discovering their preferences at a cost, which is corroborated by survey evidence.

These results highlight the advantages of dynamic multioffer mechanisms. Before students are required to rank university programs, they are allowed to hold more than one offer in the multioffer phase, which helps them optimize their preference discovery. Our proposed Batched Multioffer DA (BM-DA) mechanism, which is an improvement over the multioffer mechanism used in Germany's university admissions, captures such efficiency gains and dominates the DA, the most commonly used single-offer mechanism in real-world matching markets.

The BM-DA mechanism can be implemented through an online clearinghouse, similar to the DoSV in Germany and *Parcoursup* in France for university admissions. When implementing the BM-DA mechanism in practice, it is important to pay attention to the details of its design. For example, the choice of the number of rounds with offers in the multioffer phase should be guided by the specific context. The more time-consuming the preference discovery is, the more time students should have between rounds, *ceteris paribus*, which implies fewer rounds of offers if the total length of the multioffer phase is fixed. Moreover, highly homogeneous preferences of both students and programs imply that offers in each round are concentrated on a small group of students. Having more rounds of offers may benefit students who are ranked low by the programs. We leave the formal analysis of such considerations to future research.

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Appendix to

Preference Discovery in University Admissions: The Case for Dynamic Multioffer Mechanisms

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April 2022

List of Appendices

A Data

This appendix provides additional information about the data sets used in the empirical analysis.

A.1 DoSV Data

The *Dialogorientierten Serviceverfahren* (DoSV) data for the winter term of 2015–16 is managed by the *Stiftung für Hochschulzulassung*. It consists of several files, all of which can be linked using encrypted identifiers for students and programs.

A.1.1 Data Files

Applicants. A specific file provides information on applicants' basic sociodemographic characteristics (gender, year of birth, postal code), their *Abitur* grade, and their final admission outcome, i.e., the reason for exit, the date and time of exit, and (when relevant) the accepted program. The *Abitur* grade is available for only approximately 50% of the applicants but, as explained below (Section A.1.2), it can be inferred for a large fraction of those for whom the information is missing. Possible reasons for exit include (i) the active acceptance of an early offer; (ii) the automatic acceptance of the best offer during Phase 2; (iii) the cancellation of applications; and (iv) rejection due to application errors or rejection in the final stage for students who participated in Phase 2 but received no offer.

Programs. For each of the 465 programs that participated in the DoSV procedure in 2015–16, information is provided on the program's field of study and the university where it is located.

Applicants' rank-order lists of programs. Applicants' ROLs of programs are recorded on a daily basis throughout the duration of the DoSV procedure, i.e., between April 15 and October 5, 2015. During the Application Phase, students can apply to at most 12 university programs. By default, applications are ranked by their arrival time at the clearinghouse but students may actively change the ordering at any time before Phase 2—with the information recorded in the data.

Programs' rankings of applicants. In general, the ranking of applicants by the programs follows a quota system. The size, number, and nature of the quotas are determined by state laws and regulations, and by the universities themselves. For each quota, applicants are ranked according to quota-specific criteria. We make use of the complete rankings of applicants by the programs, including all quotas. So-called preselection quotas are filled before other quotas and are typically applied to 10–20% of a program's seats. They are open to, e.g., foreign students, applicants with professional qualifications, cases of special hardship, and minors. One of the main quotas is the *Abitur* quota (*Abiturbestenquote*) where the ranking is based on a student's average *Abitur* grade and typically applies to 20% of the seats. The Waiting Time Quota (*Wartezeitquote*) is devoted to applicants who have waited for the greatest number of semesters since obtaining the *Abitur*, and typically applies to 20% of the seats as well. Finally, the University Selection Quota (*Auswahlverfahren der Hochschulen*) tends to apply to around 60% of seats and employs criteria that are determined by the programs themselves. However, the ranking under the University Selection Quota is almost entirely determined by the students' *Abitur* grade, with an average correlation coefficient between the rankings submitted by programs and the *Abitur* grade of 0.86 across programs. The order in which the quotas are processed is specific to each university.

Program offers. The exact date and time at which offers are made by programs to applicants are recorded in a separate file.

A.1.2 Additional Information

Based on the data from the DoSV procedure, we computed a number of auxiliary variables.

***Abitur* grades.** In the data, the *Abitur* grade is available for only 49.6% of applicants. However, this information can be inferred for a large fraction of the other applicants based on how they are ranked under programs' *Abitur* quota, because these rankings are strictly determined by an applicant's *Abitur* grade. The grade is given on a 6-point scale to one place after the decimal and ranges between 1.0 (highest grade) and 6.0 (lowest grade). Since the lowest passing grade is 4.0, all applicants in the data have *Abitur* grades between 1.0 and 4.0. Due to the discreteness of the *Abitur*, missing grades can be imputed without error in the following cases: (i) an applicant is ranked above any applicant with a grade of 1.0 (in which case the assigned grade is 1.0); (ii) an applicant is ranked below any applicant with a grade equal to s and above any applicant with the same grade s (in which case the assigned grade is s); and (iii) an applicant is ranked below any applicant with a grade of 4.0 (in which case the assigned grade is 4.0). Using this procedure, we were able to impute the *Abitur* grade for approximately two thirds of applicants with a missing grade in the data, bringing the overall proportion of students with a nonmissing *Abitur* grade to 83%.

Distance to university. To measure the distance between a student's home and the university of each of the programs she applied to, we geocoded students' postal codes and university addresses, and computed the cartesian distance between the centroid of the student's postal code and the geographic coordinates of each university.

Feasible programs. A program is defined as being ex post feasible to a student if the student was ranked above the last applicant to have received an offer from the program under any of the quota-specific rankings in which the student appears. The date the program became feasible to the student i is determined as the first day when i, or any student ranked below i, received an offer from the program under any of the quota-specific rankings in which i appears.

A.1.3 Sample Restrictions

The DoSV data contain 183,028 students applying to university programs for the winter term of 2015–16. We exclude 31,066 students for whom the *Abitur* grade is missing and cannot be inferred using the procedure described above, as well as 2,252 students with missing sociodemographic or postal code information. We further remove from the sample 4,097 students who registered to the clearinghouse after the start of Phase 1. Finally, we exclude 34,832 students who applied to specific programs with complex ranking rules, these students being mostly those wanting to become teachers and who have to choose multiple subjects (e.g., math and English). This leaves us with a sample of 110,781 students.

Table 1 in the main text provides summary statistics for this sample, as well as for the subsample of students who applied to at least two programs (64,876 students). To estimate the impact of early offers on the acceptance of offers, we consider only students who applied to at least two feasible programs and either actively accepted an early offer in Phase 1 or were assigned to their best offer by the computerized algorithm in Phase 2. In total, there are 21,711 such students in the sample.

A.2 Survey

We conducted an online survey between July 27 and October 10, 2015, among students who participated in the DoSV procedure for the winter term of 2015–16. All visitors of the application website were invited to participate in the survey. We collected around 9,000 responses. Of all respondents, 52% completed the survey in July and August while 48% completed it in September and October. The survey formed part of an official survey conducted by the *Stiftung für Hochschulzulassung*, which was aimed at collecting feedback on the DoSV procedure and its website.

Our survey questions focus on the general understanding of the procedure as well as the process of preference formation, including the effect of early offers and the acquisition of information. Since students were able to participate in the survey over a long period of time, we also asked questions regarding the status of their applications, including offers received, rejected, etc. For every question, we included the option "I do not want to answer this question." In the following, we document the complete list of questions (translated from German).

1. How many programs did you apply for through the DoSV? Please provide the number.
2. How many programs did you apply for outside the DoSV? Please provide the number.
3. Which subjects did you apply for through the DoSV? [The list of all subjects grouped in clusters was shown.]
4. Did you apply to some universities in the hope of going there with your friends? [Yes/no]
5. How many offers have you already received? Please consider both offers inside the DoSV and outside of it. Please provide the number.
6. If you have already received an offer, please answer questions 7, 8, 9, and 10. If not, please proceed with question 11.
7. Regarding the offers that you have received up to now [Rate on a Likert scale]
    - Did you talk to your parents about these universities?
    - Did you talk to your friends about these universities?
    - Did you talk to your friends about the possibility of accepting offers at the same university or at universities that are located close to each other?
8. When comparing universities that have made you an offer with universities that have not, can it then be said that [Choose one option]

- On average, I spend more time collecting information on the universities that have made me an offer.
- On average, I spend the same amount of time collecting information on the universities that have made me an offer.
- On average, I spend less time collecting information on the universities that have made me an offer.

9. Regarding the universities that have already made you an offer, which of the following statements best describes your situation? [Choose one option]
    - On average, I find these universities better than before receiving their offers.
    - I find some of these universities better and some worse than before receiving their offers.
    - On average, I find these universities worse than before receiving their offers.
    - The offers did not influence my evaluation of the universities.
10. What is your opinion regarding the acceptance of one of the offers that you have already received? [Rate on a Likert scale]
    - I will accept (or have already accepted) one of the offers since it is from my most preferred university.
    - I will accept (or have already accepted) one of the offers in order to be able to start planning future activities as soon as possible.
    - I will take my time since I want to find out more about the universities.
    - I will take my time since I want to find out where my friends are going to study.
    - I will take my time since I have not received an offer from my preferred university yet.
11. Have any of your friends already received an offer? [Yes/no]
12. If yes, did any of your friends... [Rate on a Likert scale]
    - ... talk to you about the advantages and disadvantages of these universities?
    - ... talk to you about accepting one of these offers?
    - ... consider the possibility of accepting one of the offers from the same or a nearby university together with you or some other friends?
13. Please remember the situation when you submitted your applications to the universities in the DoSV. We would like to know how well you knew at this point how to rank your applications, that is, which application was your most preferred, your second preferred, etc. How accurate are the following statements regarding your situation back then with respect to your preference ranking over the programs? [Rate on a Likert scale]
    - I had a clear preference ranking over the programs.
    - I did not have a clear ranking because I still needed to collect information in order to rank my applications according to my preferences.
    - I did not have a clear ranking because I did not know where my friends were going.
    - Getting to a ranking was very difficult, and I wanted to postpone this decision for as long as possible.
14. Did you actively change your ranking in the DoSV (that is, submitted a new ranking or actively prioritized the applications)? [Yes/no]
15. If no, please provide us with the reasons. [Rate on a Likert scale]

- I did not know that it was possible to change the ranking.
- I was happy with the initial ranking of the DoSV.
- I missed the deadline before which it was possible to change the ranking.
- I did not have a clear ranking of my applications.
- I assume that the ranking has no effect on the likelihood of being admitted.

16. Has your ranking changed between the beginning of the procedure on July 15 and now? [Yes/no]
17. If yes, what were the reasons for changing your ranking? [Rate on a Likert scale]
    - I did not have a ranking at the beginning of the procedure when I submitted my applications.
    - I have received new information during this time period.
    - Now I know where my friends are going.
    - I have received some early offers that have changed my perception of the universities.
18. Have you tried to collect information about the universities during the procedure, in particular... [Rate on a Likert scale]
    - ... via the internet?
    - ... from students of these universities?
    - ... from your school teachers?
    - ... from your parents or other members of your family?
    - ... from your friends?
19. Which of the following reasons have played a role for your selection of programs and universities and for your ranking of them? [Rate on a Likert scale]
    - The fit between the program offered by the university and my own interests.
    - The geographical proximity to my parents.
    - The geographical proximity to my friends.
    - Job market considerations.
    - Whether my application has a chance of being successful at this university.
    - Other reasons.
20. Please tell us your gender. [Female/male]

B Supplementary Figures and Tables

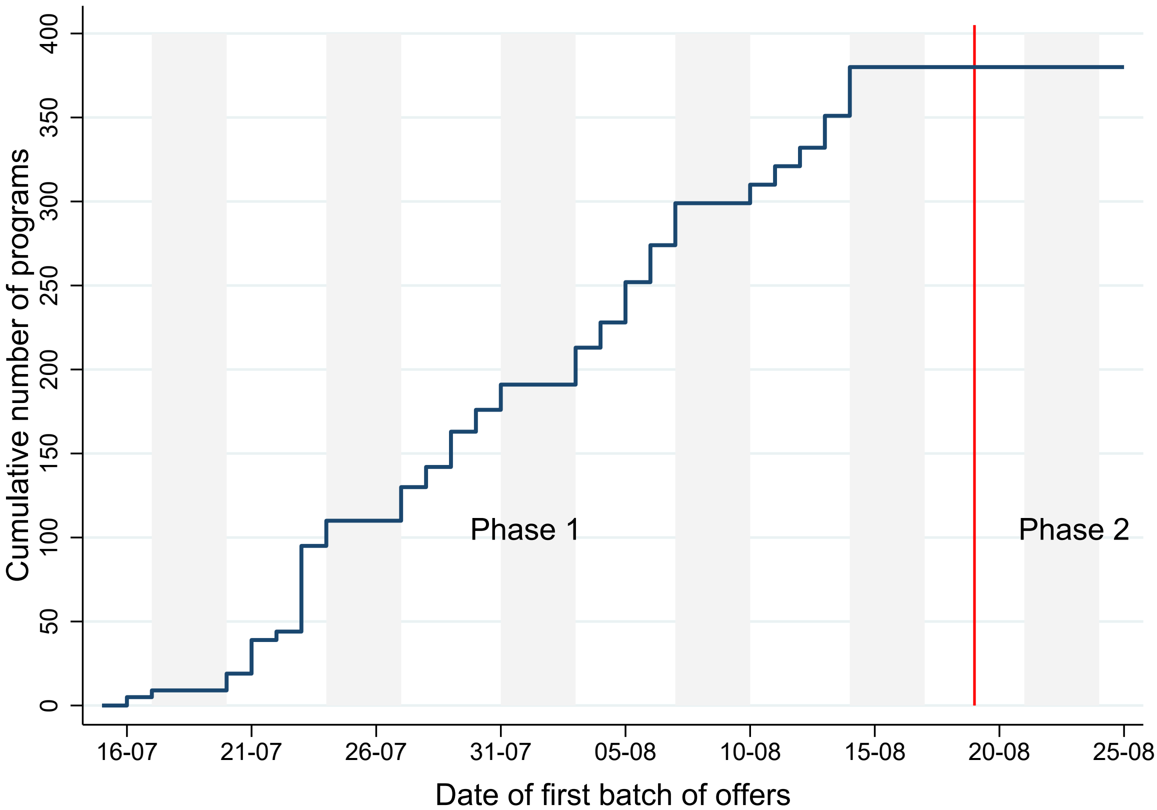

Figure B1 – First Batch of Offers Sent Out by Programs

Notes: This figure shows the cumulative number of programs that have made their first round of offers throughout Phase 1 of the DoSV procedure, i.e., between July 16 and August 18, 2105, based on data from the winter term of 2015–16. Weekends—during which no first round of offers are sent by university programs—are denoted by gray shaded areas.

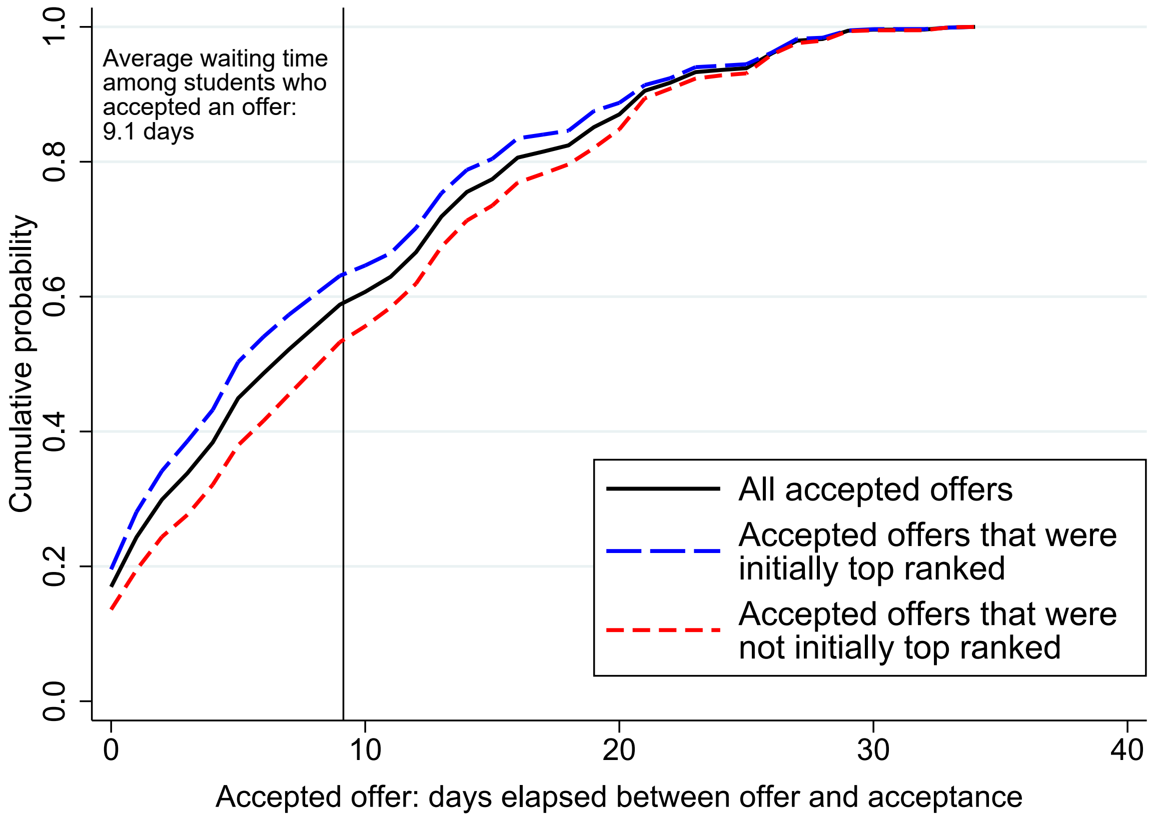

Figure B2 – Accepted Offer: Cumulative Distribution of Number of Days Elapsed between Offer and Acceptance

Notes: This figure shows the cumulative empirical distribution of the number of days elapsed between the date an offer is received by a student and the date it is accepted. The sample is restricted to students who applied to at least two feasible programs and either actively accepted an early offer during Phase 1 or were assigned to their best offer by the computerized algorithm in Phase 2. The different lines correspond to different subsets of accepted offers: (i) all accepted offers (solid line); (ii) accepted offers that were initially top ranked by students (long-dashed line); and (iii) accepted offers that were not initially top ranked by students (short-dashed line).

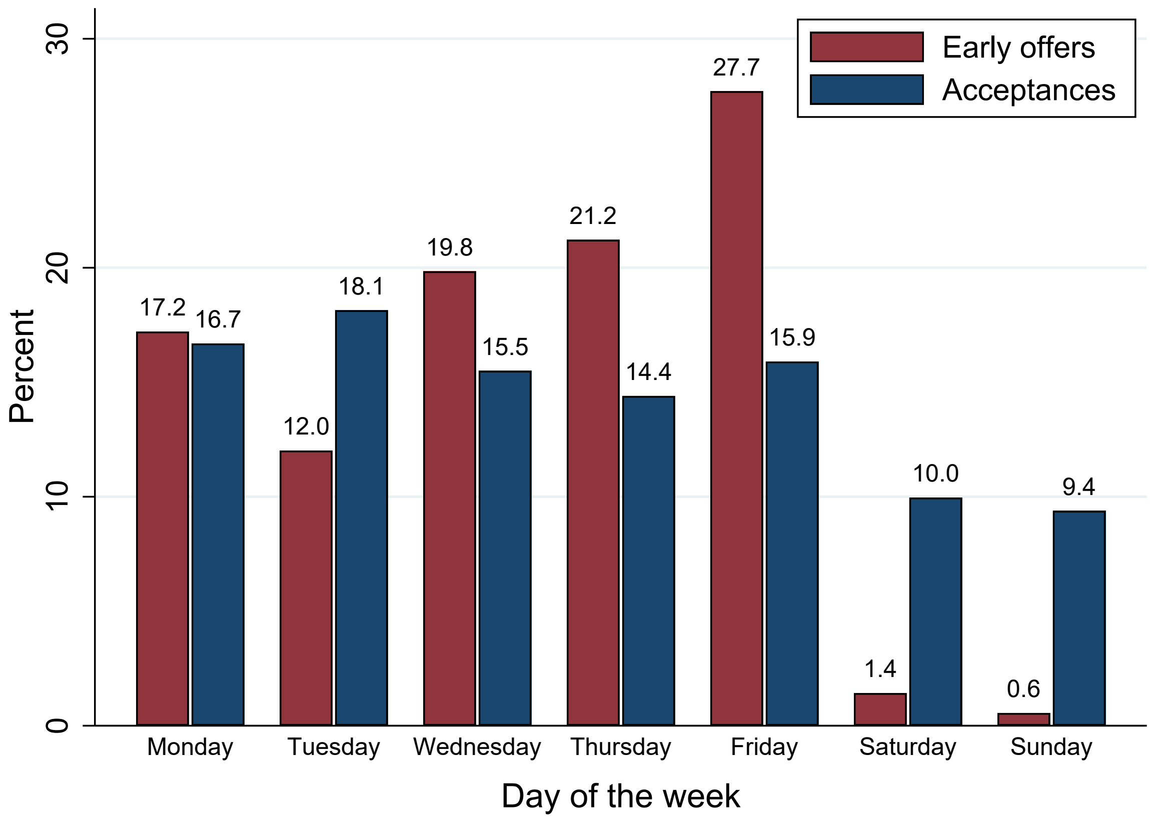

Figure B3 – Distribution of Early Offers and Acceptances across the Days of the Week

Notes: This figure shows the distribution of early offers and acceptances during Phase 1 of the DoSV procedure (i.e., between Thursday, July 16 and Tuesday, August 18, 2015), across the days of the week. The proportions are adjusted to account for the fact that the distribution of days of the week is not balanced during the period (all days but Wednesday have 5 occurrences each whereas Wednesday has 4 occurrences).

Table B1 – Early Offer and Acceptance among Feasible Programs: Heterogeneity Analysis

	(1)	(2)	(3)	(4)	(5)
EarlyOffer: Potential offer from program in Phase 1	0.424***	0.568***	0.529***	0.432***	0.592***
	(0.108)	(0.122)	(0.162)	(0.115)	(0.164)
× female student		−0.202**			−0.196**
		(0.081)			(0.084)
× *Abitur* percentile (between zero and one)			−0.109		−0.022
			(0.155)		(0.165)
× number of feasible programs (in excess of two)				−0.005	0.004
				(0.024)	(0.025)
FirstEarlyOffer: First offer in Phase 1	0.147***	0.176***	0.326***	0.152***	0.339***
	(0.023)	(0.031)	(0.051)	(0.026)	(0.054)
× female student		−0.051			−0.029
		(0.036)			(0.036)
× *Abitur* percentile (between zero and one)			−0.268***		−0.258***
			(0.068)		(0.069)
× number of feasible programs (in excess of two)				−0.007	−0.002
				(0.013)	(0.013)
Controls					
Distance to university (quadratic)	Yes	Yes	Yes	Yes	Yes
Program in student's region (*Land*)	Yes	Yes	Yes	Yes	Yes
Program's ranking of student (between zero and one)	Yes	Yes	Yes	Yes	Yes
Chances of not receiving an offer from program in Phase 2	Yes	Yes	Yes	Yes	Yes
Program fixed effects (376 programs)	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263

Notes: This table reports estimates from a conditional logit model for the probability of accepting a program among feasible programs. The sample and variables are the same as in Table 3 in the main text. Standard errors are shown in parentheses. **: p <0.05; ***: p <0.01.

Table B2 – Early Offer and Acceptance among Feasible Programs: Robustness to Contracting Students' Feasible Sets

	Contracted feasible sets: a program is considered as feasible if the student's rank $\leqslant \bar{r} \times$ admission cutoff rank (with $\bar{r} \leqslant 1$)					
	$\bar{r}$ = 1.0	$\bar{r}$ = 0.9	$\bar{r}$ = 0.8	$\bar{r}$ = 0.7	$\bar{r}$ = 0.6	$\bar{r}$ = 0.5
	(1)	(2)	(3)	(4)	(5)	(6)
A. Estimates						
EarlyOffer: Potential offer from program in Phase 1	0.404***	0.459***	0.465***	0.460***	0.478***	0.681***
	(0.044)	(0.053)	(0.069)	(0.097)	(0.154)	(0.239)
FirstEarlyOffer: First offer in Phase 1	0.147***	0.137***	0.134***	0.131***	0.127***	0.125***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)
Distance to university (thousands of km)	−9.37***	−9.35***	−9.31***	−9.39***	−9.42***	−9.40***
	(0.33)	(0.34)	(0.34)	(0.34)	(0.35)	(0.35)
Distance to university squared	12.54***	12.53***	12.41***	12.42***	12.49***	12.45***
	(0.55)	(0.56)	(0.56)	(0.57)	(0.57)	(0.57)
Program in student's region (*Land*)	−0.006	−0.004	0.011	−0.008	−0.017	−0.021
	(0.039)	(0.040)	(0.040)	(0.041)	(0.041)	(0.041)
Program's ranking of student (between zero and one)	0.439*	0.440*	0.492**	0.361	0.402*	0.407*
	(0.227)	(0.231)	(0.236)	(0.239)	(0.240)	(0.241)
Program fixed effects (376)	Yes	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	20,911	20,300	19,925	19,713	19,627
Total number of feasible programs	66,263	63,523	61,358	59,986	59,218	58,925
B. Marginal effects on acceptance probability of feasible programs						
Baseline (no early offer) acceptance probability	0.385	0.386	0.387	0.388	0.388	0.389
Nonfirst early offer (percentage points)	8.3	9.4	9.5	9.4	9.8	14.1
	(1.5)	(1.7)	(1.7)	(1.7)	(1.8)	(2.4)
First early offer (percentage points)	11.3	12.3	12.3	12.2	12.5	16.6
	(2.0)	(2.1)	(2.1)	(2.1)	(2.2)	(2.7)

Notes: The sample and variables are the same as in Table 3 in the main text. This table shows the results based on the specification in column 4 of Table 3 when we artificially contract students' sets of feasible programs. We proceed by relabelling as "infeasible" from the student's perspective any program that a student included in her initial ROL and whose cutoff was barely cleared by the student in Phase 2. Starting from the main analysis sample, we modify students' feasible sets and acceptance decisions as follows: (i) we relabel as "infeasible" any program that became feasible to the student in Phase 2 and for which the ratio r between the student's rank under the most favorable quota and the rank of the last student who received an offer from the program under that quota is between $\bar{r}$ and 1, with $\bar{r} < 1$ (the most favorable quota is the quota under which the program first became feasible to the student); (ii) we restrict the sample to students who applied to at least two feasible programs under the new definition of program feasibility; (iii) if the student accepted an offer from a program that became feasible in Phase 2 but is no longer feasible under the new definition, we modify the student's acceptance decision by considering that the student accepted the highest ranked offer among the programs that she ranked upon entering Phase 2 and that remain feasible under the new definition of feasibility. The baseline estimates obtained using the observed (ex post) feasible sets of programs are reported in column 1. The results using the contracted feasible sets are shown in columns 2–6 for various choices of the upper limit $\bar{r}$ between 0.5 and 0.9. Standard errors are shown in parentheses. *: p <0.1; **: p <0.05; ***: p <0.01.

Table B3 – Early Offer and Acceptance among Feasible Programs: Robustness to Expanding Students' Feasible Sets

	Expanded feasible sets: a program is considered as feasible if the student's rank $\leqslant \overline{r} \times$ admission cutoff rank (with $\overline{r} \geqslant 1$)					
	$\overline{r} = 1.0$	$\overline{r} = 1.1$	$\overline{r} = 1.2$	$\overline{r} = 1.3$	$\overline{r} = 1.4$	$\overline{r} = 1.5$
	(1)	(2)	(3)	(4)	(5)	(6)
A. Estimates						
EarlyOffer: Potential offer from program in Phase 1	0.404***	0.564***	0.654***	0.711***	0.752***	0.768***
	(0.044)	(0.034)	(0.030)	(0.029)	(0.027)	(0.027)
FirstEarlyOffer: First offer in Phase 1	0.147***	0.152***	0.145***	0.130***	0.117***	0.116***
	(0.023)	(0.022)	(0.021)	(0.021)	(0.021)	(0.020)
Distance to university (thousands of km)	−9.37***	−9.36***	−9.09***	−9.05***	−8.90***	−8.83***
	(0.33)	(0.31)	(0.30)	(0.29)	(0.28)	(0.28)
Distance to university squared	12.54***	12.52***	12.05***	12.00***	11.83***	11.70***
	(0.55)	(0.52)	(0.50)	(0.49)	(0.47)	(0.46)
Program in student's region (*Land*)	−0.006	0.008	0.021	0.026	0.021	0.033
	(0.039)	(0.037)	(0.036)	(0.034)	(0.033)	(0.033)
Program's ranking of student (between zero and one)	0.439*	0.463**	0.490**	0.568***	0.545***	0.531***
	(0.227)	(0.217)	(0.209)	(0.203)	(0.197)	(0.192)
Program fixed effects (376)	Yes	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	23,513	25,101	26,590	27,915	29,159
Total number of feasible programs	66,263	72,521	78,508	84,154	89,610	94,677
B. Marginal effects on acceptance probability of feasible programs						
Baseline (no early offer) acceptance probability	0.385	0.382	0.379	0.376	0.373	0.370
Nonfirst early offer (percentage points)	8.3	11.7	13.5	14.8	15.6	15.9
	(1.5)	(2.0)	(2.3)	(2.4)	(2.5)	(2.5)
First early offer (percentage points)	11.3	14.8	16.6	17.5	18.1	18.4
	(2.0)	(2.4)	(2.6)	(2.7)	(2.7)	(2.8)

Notes: The sample and variables are the same as in Table 3 in the main text. This table shows the results based on the specification in column 4 of Table 3 when we artificially expand students' sets of feasible programs. We proceed by relabelling as "feasible" from the student's perspective any program that a student included in her initial ROL and whose cutoff was barely missed by the student in Phase 2. Starting from the sample of students who applied to at least two programs (not necessarily feasible) and did not cancel their application at some point during the procedure, we modify students' feasible sets and acceptance decisions as follows: (i) we relabel as "feasible" any program for which the ratio r between the student's rank under the most favorable quota and the rank of the last student who received an offer from the program under that quota is at most $\overline{r}$, with $\overline{r} > 1$ (the most favorable quota is approximated as the quota under which the ratio r is he smallest for the student); (ii) we restrict the sample to students who applied to at least two feasible programs under the new definition of program feasibility; (iii) if the student participated in Phase 2 and would have been assigned to program j under the new definition of feasibility, i.e., if program j is the highest-ranked feasible program in the student's final ROL, the student is considered as having accepted an offer from that program. The baseline estimates using the observed (ex post) feasible sets of programs are reported in column 1. The results using the expanded feasible sets are shown in columns 2–6 for various choices of the upper limit $\overline{r}$ between 1.1 and 1.5. Standard errors are shown in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Table B4 – Early Offer and Acceptance among Feasible Programs: By Week in which Program Became Feasible

	(1)	(2)	(3)	(4)	(5)
EarlyOffer: Potential offer from program in Phase 1					
× Weeks 1, 2	0.790***	0.838***	0.817***	0.810***	0.800***
	(0.060)	(0.075)	(0.076)	(0.076)	(0.123)
× Weeks 3–5	0.434***	0.372***	0.375***	0.367***	0.356***
	(0.042)	(0.044)	(0.044)	(0.044)	(0.109)
FirstEarlyOffer: First offer in Phase 1					
× Weeks 1, 2		−0.111**	−0.090*	−0.090*	−0.090*
		(0.047)	(0.048)	(0.048)	(0.048)
× Weeks 3–5		0.152***	0.169***	0.168***	0.168***
		(0.028)	(0.029)	(0.029)	(0.029)
Distance to university (thousands of km)			−9.35***	−9.36***	−9.36***
			(0.33)	(0.33)	(0.33)
Distance to university squared			12.51***	12.53***	12.53***
			(0.55)	(0.55)	(0.55)
Program in student's region (*Land*)			−0.007	−0.008	−0.008
			(0.039)	(0.039)	(0.039)
Program's ranking of student (between zero and one)				0.445*	0.444*
				(0.227)	(0.227)
Chances of not receiving an offer from program in Phase 2					−0.009
					(0.076)
Program fixed effects (376 programs)	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263

Notes: This table reports estimates from a conditional logit model for the probability of accepting an offer from a feasible program. The sample and variables are the same as in Table 3 in the main text. Standard errors are shown in parentheses. *: p <0.1; **: p <0.05; ***: p <0.01.

Table B5 – Acceptance among Feasible Programs and Final ROLs: Controlling for How Students Initially Rank Programs

	Acceptance among feasible (conditional logit) (1)	Final ROL (rank-ordered logit) (2)
EarlyOffer: Potential offer from program in Phase 1	0.707***	0.653***
	(0.134)	(0.130)
FirstEarlyOffer: First offer in Phase 1	0.189***	0.169***
	(0.028)	(0.027)
Distance to university (thousands of km)	−6.54***	−6.35***
	(0.39)	(0.38)
Distance to university squared	8.55***	8.23***
	(0.66)	(0.64)
Program in student's region (*Land*)	−0.032	−0.021
	(0.047)	(0.046)
Program's ranking of student (between zero and one)	0.534*	0.549**
	(0.274)	(0.271)
Chances of not receiving an offer from program in Phase 2	0.050	0.052
	(0.095)	(0.092)
Student's initial ranking of program (ref.: rank=1)		
rank=2	−1.422***	−1.410***
	(0.022)	(0.022)
rank=3	−2.043***	−2.039***
	(0.032)	(0.031)
rank=4	−2.358***	−2.362***
	(0.041)	(0.040)
rank=5 or above	−3.051***	−3.068***
	(0.042)	(0.041)
Program fixed effects (376 programs)	Yes	Yes
Number of students	21,711	21,711
Total number of feasible programs	66,263	66,263

Notes: The sample and variables are the same as in Table 3 in the main text. Column 1 reports estimates from a conditional logit model for the probability of accepting an offer from a feasible program. Column 2 reports estimates from a rank-ordered logit model for the probability of observing a student's final rank-order list (ROL), using only the payoff-relevant information in each ROL. Standard errors are shown in parentheses. *: p <0.1; **: p <0.05; ***: p <0.01.

Table B6 – Initial vs. Final Ranking of Feasible Programs: Students who Submitted an Initial ROL that they Reranked in the Application Phase

	Rank-order list					
	Initial ROL (at start of Phase 1)			Final ROL (at end of Phase 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
EarlyOffer: Potential offer from program in Phase 1	−0.069	−0.051	−0.069	0.490***	0.450***	0.604***
	(0.043)	(0.044)	(0.125)	(0.067)	(0.070)	(0.186)
FirstEarlyOffer: First offer in Phase 1		−0.050*	−0.035		0.080*	0.108***
		(0.027)	(0.027)		(0.041)	(0.042)
Distance to university (thousands of km)			−5.19***			−9.85***
			(0.33)			(0.55)
Distance to university squared			6.53***			12.33***
			(0.55)			(0.90)
Program is in student's region (*Land*)			−0.007			−0.001
			(0.042)			(0.065)
Program's ranking of student (between zero and one)			−0.001			−0.032
			(0.278)			(0.453)
Chances of not receiving an offer from program in Phase 2			0.011			0.131
			(0.091)			(0.133)
Program fixed effects (364)	Yes	Yes	Yes	Yes	Yes	Yes
Number of students	6,473	6,473	6,473	6,473	6,473	6,473
Total number of feasible programs	23,116	23,116	23,116	23,116	23,116	23,116

Notes: This table repeats the same analysis as in Table 4 in the main text on a restricted sample. The sample here includes only students who applied to at least two feasible programs, who submitted an initial ROL that they reranked at some point in the Application Phase (i.e., before Phase 1), and actively accepted an early offer during Phase 1 or were assigned to their best offer by the computerized algorithm in Phase 2. Standard errors are shown in parentheses. *: $p < 0.1$; ***: $p < 0.01$.

Table B7 – How Long do Students Wait before Accepting an Offer?

	Dependent variable: number of days between offer arrival and acceptance	
	Sample 1: Students with a least two feasible programs who actively accepted an offer in Phase 1	Sample 2: Sample 1 + students who were automatically assigned to a program in Phase 2
	(1)	(2)
Intercept[a]	11.17***	18.17***
	(0.17)	(0.15)
Female	−0.228*	0.004
	(0.100)	(0.088)
Abitur percentile (between zero and one)	0.270	−0.369*
	(0.182)	(0.162)
Distance to university (thousands of km)	4.99***	15.91***
	(1.31)	(1.10)
Distance to university squared	−8.02***	−24.40***
	(2.41)	(1.98)
Program is not in student's region (*Land*)	0.032	0.365**
	(0.138)	(0.121)
Student's initial ranking of program (ref.: rank=1)		
rank = 2	2.637***	1.150***
	(0.125)	(0.113)
rank = 3	2.855***	1.615***
	(0.176)	(0.155)
rank = 4	3.590***	1.841***
	(0.229)	(0.202)
rank=5 or above	3.566***	2.166***
	(0.212)	(0.183)
Number of days between start of Phase 1 and date of offer arrival	−0.419***	−0.597***
	(0.006)	(0.005)
Number of programs in initial ROL (in excess of 2)	0.086***	0.046*
	(0.024)	(0.021)
Number of other offers held when accepting offer	0.659***	0.579***
	(0.039)	(0.036)
Number of observations	12,025	21,711
Adjusted R-squared	0.343	0.435
Mean waiting time before accepting offer (in days)	6.67	9.11
	(6.50)	(8.30)

Notes: This table reports estimates from a regression where the dependent variable is the number of days between the date an offer was received by a student and the date it was accepted. The sample in column 1 includes students who applied to at least two feasible programs and actively accepted an early offer in Phase 1. The sample in column 2 further includes students who were assigned to their best offer by the computerized algorithm in Phase 2 (with an acceptance date set to the first day of Phase 2, i.e., August 19, 2015). Standard errors are shown in parentheses. *: $p<0.1$; **: $p<0.05$; ***: $p<0.01$.

[a] The regression intercept can be interpreted as the mean waiting time before accepting an offer that was received by a male student at the lowest percentile of the *Abitur* grade distribution, from a program located in the student's region, that was initially ranked in first position in a two-choice rank-order list, when the offer arrives on the first day of Phase 1 and no other offers are held.

Table B8 – Early Offer and Acceptance among Feasible Programs: Using Flexible Controls for a Program's Ranking of the Student

	(1)	(2)	(3)	(4)	(5)
A. Estimates					
EarlyOffer: Potential offer from program in Phase 1	0.424***	0.455***	0.454***	0.436***	0.443***
	(0.108)	(0.109)	(0.109)	(0.108)	(0.109)
FirstEarlyOffer: First offer in Phase 1	0.147***	0.153***	0.154***	0.148***	0.151***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Distance to university (thousands of km)	−9.37***	−9.41***	−9.41***	−9.39***	−9.39***
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
Distance to university squared	12.54***	12.60***	12.60***	12.57***	12.58***
	(0.55)	(0.55)	(0.55)	(0.55)	(0.55)
Program in student's region (*Land*)	−0.006	−0.006	−0.005	−0.005	−0.005
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Chances of not receiving an offer from program in Phase 2	0.016	0.024	0.022	0.018	0.021
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
Program's ranking of student (between zero and one)	Linear	Quadratic	Quartic	Quartiles	Deciles
Program fixed effects (376)	Yes	Yes	Yes	Yes	Yes
Number of students	21,711	21,711	21,711	21,711	21,711
Total number of feasible programs	66,263	66,263	66,263	66,263	66,263
B. Marginal effects on acceptance probability of feasible programs					
Baseline (no early offer) acceptance probability: 38.5%					
Nonfirst early offer (percentage points)	8.7	9.3	9.3	8.9	9.1
	(1.6)	(1.7)	(1.7)	(1.7)	(1.7)
First early offer (percentage points)	11.8	12.5	12.5	12.0	12.2
	(2.1)	(2.2)	(2.2)	(2.1)	(2.1)

Notes: The sample and variables are the same as in Table 3 in the main text. This table shows the results obtained when using alternative ways of controlling for a program's ranking of the student, which is measured as the student's percentile (between zero and one, with a higher value indicating a better rank) among all applicants under the *Abitur* quota: a linear control (column 1, which replicates column 5 of Table 3); a quartic (column 2) or quadratic (column 3) function; dummies for quartiles of this variable (column 4); and dummies for deciles (column 5). Standard errors are shown in parentheses. ***: $p < 0.01$.

Table B9 – Early Offer and Acceptance among Feasible Programs: Students who Applied only to Programs Located in their Municipality of Residence

	(1)	(2)	(3)
A. Estimates			
EarlyOffer: Potential offer from program in Phase 1	0.661***	0.466***	0.461***
	(0.121)	(0.131)	(0.131)
FirstEarlyOffer: First offer in Phase 1		0.312***	0.307***
		(0.079)	(0.079)
Program's ranking of student (between zero and one)			0.289
			(0.649)
Program fixed effects (273 programs)	Yes	Yes	Yes
Number of students	2,459	2,459	2,459
Total number of feasible programs	6,612	6,612	6,612
B. Marginal effects on acceptance probability of feasible programs			
Baseline (no early offer) acceptance probability: 41.5%			
Nonfirst early offer (percentage points)	13.7	9.6	9.5
	(3.3)	(2.4)	(2.4)
First early offer (percentage points)		16.0	15.7
		(3.9)	(3.9)

Notes: This table repeats the same analysis as in Table 3 on a restricted sample. The sample is restricted to students who applied only to programs located in their municipality of residence. Standard errors are shown in parentheses. ***: p <0.01.

Table B10 – Early Offer and Acceptance among Feasible Programs: Students who Did not Accept an Early Offer until at least Halfway Through Phase 1

	(1)	(2)	(3)	(4)	(5)
A. Estimates					
EarlyOffer: Potential offer from program in Phase 1	0.446***	0.411***	0.410***	0.405***	0.412***
	(0.042)	(0.044)	(0.045)	(0.045)	(0.109)
FirstEarlyOffer: First offer in Phase 1		0.063***	0.078***	0.077***	0.077***
		(0.023)	(0.024)	(0.024)	(0.024)
Distance to university (thousands of km)			−8.77***	−8.78***	−8.78***
			(0.34)	(0.34)	(0.34)
Distance to university squared			11.62***	11.63***	11.63***
			(0.56)	(0.56)	(0.56)
Program in student's region (*Land*)			−0.002	−0.003	−0.003
			(0.040)	(0.040)	(0.040)
Program's ranking of student (between zero and one)				0.346	0.347
				(0.237)	(0.237)
Chances of not receiving an offer from program in Phase 2					0.006
					(0.076)
Program fixed effects (273 programs)	Yes	Yes	Yes	Yes	Yes
Number of students	19,693	19,693	19,693	19,693	19,693
Total number of feasible programs	60,394	60,394	60,394	60,394	60,394
B. Marginal effects on acceptance probability of feasible programs					
Baseline (no early offer) acceptance probability: 38.4%					
Nonfirst early offer (percentage points)	9.5	8.7	8.4	8.3	8.4
	(1.5)	(1.4)	(1.6)	(1.5)	(1.6)
First early offer (percentage points)		10.1	10.0	9.9	10.1
		(1.5)	(1.8)	(1.8)	(1.8)

Notes: This table repeats the same analysis as in Table 3 on a restricted sample. The sample is restricted to students who did not accept an early offer until at least halfway through Phase 1, i.e., until August 2 (Phase 1 lasted 34 days, from July 16 to August 18). Standard errors are shown in parentheses. ***: $p < 0.01$.

C Early-Offer Effect: Regression Discontinuity Estimates

This appendix uses a regression discontinuity (RD) design to provide supplementary evidence that early offers are accepted more often than later ones. This design exploits the fact that a student's receipt of an early offer during Phase 1 of the DoSV procedure is determined by the student's position in the program's ranking of its applicants. The effect of early offers on the acceptance probability can therefore be estimated by comparing the acceptance behavior of students ranked just above versus just below a program's Phase 1 cutoff rank, i.e., the rank of the last student who received an early offer from the program in Phase 1.

Limitations of the RD design in the DoSV setting. The reason why we do not adopt an RD design as our main empirical strategy is that it has a number of limitations in our setting.

A first limitation comes from the fact that in the DoSV procedure, each program has several quotas (the average program has six) and an applicant appears on multiple rankings of the same program, e.g., the one for the *Abitur* quota (*Abiturbestenquote*) and the one for the Waiting time quota (*Wartezeitquote*). An undesirable consequence of these multiple rankings is that a student who missed a program's Phase 1 cutoff under quota q can receive an early offer from the program under a different quota q' provided that she clears this other quota's cutoff by the end of Phase 1. As a result, the RD design is fuzzy rather than sharp—the observed discontinuity in the probability of receiving a potential early offer at the Phase 1 cutoff of a program's quota is less than one.

A second limitation of the RD design is that the comparison of students' acceptance decisions around the Phase 1 cutoffs allows us to estimate only the early-offer effect on the probability of accepting a program and not to compare the effects of the first versus subsequent early offers or to analyze students' reranking behavior.

A third limitation is that the RD design identifies the early-offer effect only for the subgroup of students who barely cleared or barely missed the cutoff to receive an early offer, whereas we are interested in estimating this effect for a broader population of applicants.

Sample restrictions. Bearing in mind these limitations, we implement a fuzzy RD design by restricting the sample to the subset of students and programs for which this approach can be applied. We start by considering all programs that made offers in both Phase 1 and Phase 2 and keep only the relevant quotas, i.e., those under which offers were made in both phases. Let $\overline{R}^1_{j,q}$ denote the rank of the last student who received an offer from program j under quota q by the end of Phase 1, and let $\overline{R}^2_{j,q}$ denote the rank of the last applicant who received an offer from program j under quota q by the end of Phase 2. By construction, $\overline{R}^2_{j,q} \geqslant \overline{R}^1_{j,q}$. We restrict the set of program quotas (j, q) to those having at least 10 applicants ranked above the Phase 1 cutoff ($\overline{R}^1_{j,q}$) and at least 10 applicants ranked between the Phase 1 and Phase 2 cutoffs (i.e., between $\overline{R}^1_{j,q}$ and $\overline{R}^2_{j,q}$). To ensure consistency with our main empirical results, we consider only students who applied to at least two feasible programs and accepted an offer.

Empirical specification. Our RD estimates of the early-offer effect are based on the following empirical specification:

$$Accept_{i,j,q} = \delta \, EarlyOffer_{i,j,q} + f(\tilde{R}^1_{i,j,q}) + \epsilon_{i,j,q}, \quad \text{(A.1)}$$
$$EarlyOffer_{i,j,q} = \pi \mathbb{1}\{\tilde{R}^1_{i,j,q} \leqslant 0\} + g(\tilde{R}^1_{i,j,q}) + \nu_{i,j,q}, \quad \text{(A.2)}$$

where $Accept_{i,j,q}$ is an indicator that equals one if student i, ranked under program quota (j,q), accepted an offer (in Phase 1 or Phase 2) from program j under any quota; $EarlyOffer_{i,j,q}$ is an indicator that takes the value one if the student had a potential early offer (i.e., before the end of Phase 1) from program j under any quota; the forcing variable $\tilde{R}^1_{i,j,q} \equiv R_{i,j,q} - \overline{R}^1_{j,q}$ is the distance between the student's rank under the program quota (j,q) and the rank of the last student who received an offer in Phase 1 under that quota; $\mathbb{1}\{\tilde{R}^1_{i,j,q} \leqslant 0\}$ is an indicator that is equal to one if the student cleared the Phase 1 cutoff for program j under quota q, and hence was eligible to receive an early offer from the program under that quota; $f(\cdot)$ and $g(\cdot)$ are polynomial functions of the forcing variable $\tilde{R}^1_{i,j,q}$.

The RD instrumental variable estimator using $\mathbb{1}\{\tilde{R}^1_{i,j,q} \leqslant 0\}$ as an instrument for $EarlyOffer_{i,j,q}$ identifies the local average treatment effect of early offers on the acceptance probability under two main assumptions: (i) $\mathbb{E}(\epsilon_{i,j,q}|\tilde{R}^1_{i,j,q})$ and $\mathbb{E}(\nu_{i,j,q}|\tilde{R}^1_{i,j,q})$ are continuous, i.e., the assignment of students on either side of Phase 1 cutoff is as good as random; (ii) crossing the cutoff affects students' acceptance probability only through the increased probability of receiving an early offer.

We implemented this fuzzy RD design using the statistical package `rdrobust` described in Calonico et al. (2017). We present estimates from data-driven bandwidths that are mean square error (MSE)-optimal as proposed by Imbens and Kalyanaraman (2012) as well as the bias-corrected estimates and robust standard errors proposed by Calonico, Cattaneo and Titiunik (2014). Since a student can be ranked under multiple program quotas, standard errors are clustered at the individual level using the nearest neighbor variance estimation method described in the same study.

The linear reduced-form specifications for observations within a distance h of the Phase 1 cutoff are as follows:

$$EarlyOffer_{i,j,q} = \pi \mathbb{1}\{\tilde{R}^1_{i,j,q} \leqslant 0\} + \rho_0 + \rho_1 \tilde{R}^1_{i,j,q} + \rho_2 \tilde{R}^1_{i,j,q} \times \mathbb{1}\{\tilde{R}^1_{i,j,q} \leqslant 0\} + \eta_{i,j,q}, \quad \text{(A.3)}$$
$$Accept_{i,j,q} = \gamma \mathbb{1}\{\tilde{R}^1_{i,j,q} \leqslant 0\} + \lambda_0 + \lambda_1 \tilde{R}^1_{i,j,q} + \lambda_2 \tilde{R}^1_{i,j,q} \times \mathbb{1}\{\tilde{R}^1_{i,j,q} \leqslant 0\} + \xi_{i,j,q}, \quad \text{(A.4)}$$

where $\gamma = \delta \times \pi$.

Note that, by construction, the probability of receiving an early offer is equal to one for the last student who received an offer in Phase 1. To mitigate concerns arising from this endogenous stopping rule, we follow the recommendation in de Chaisemartin and Behaghel (2020) of dropping the last applicant who received an offer in Phase 1.[A.1]

Graphical evidence. Figure C1 plots the density of applicants on either side of the Phase 1 cutoffs, after pooling all program quotas and centering their cutoffs at 0. The manipulation testing procedure is implemented using the local polynomial density estimators proposed by Cattaneo, Jansson and Ma (2020). The results show no statistical evidence

[A.1] The authors consider the closely related problem of estimating treatment effects allocated by randomized waiting lists.

against the null hypothesis that the density is smooth around the Phase 1 cutoff.[A.2]

Panel A of Figure C2 provides graphical evidence of the first stage, i.e., the discontinuity in the probability of receiving a potential early offer when crossing the Phase 1 cutoff of a program's quota. The x-axis represents the distance between a student's rank under the program's quota and the Phase 1 cutoff rank for this quota. The graphical evidence shows that the early-offer probability increases discontinuously for students who barely cleared the Phase 1 cutoff. The induced discontinuity is smaller than one because some students who barely missed the cutoff for the considered program quota were ranked above the Phase 1 cutoff for a different quota of the same program, and hence could receive an early offer from that program.

Panel B of Figure C2 presents graphical evidence of the discontinuity in the probability of accepting program j at the Phase 1 cutoff for a quota of the program. There is clear evidence that the acceptance probability increases discontinuously for students who barely cleared the cutoff.

RD estimates of the early-offer effect. Table C1 presents the results. The specifications in columns 1 and 2 do not include covariates whereas those in columns 3 and 4 include program-quota fixed effects. Columns 1 and 3 uses the mean-squared-error-optimal bandwidth following Imbens and Kalyanaraman (2012). Columns 2 and 4 in addition report bias-corrected estimates and robust standard errors following Calonico, Cattaneo and Titiunik (2014). Standard errors are clustered at the student level using the nearest neighbor variance estimation method described in the same study.

Panel A reports first-stage RD estimates of the discontinuity in the probability of receiving an early offer from a program when crossing the Phase 1 cutoff of a program's quota. The results indicate that the early-offer probability increases significantly at the cutoff, by 76.2 to 76.4 percentage points from a baseline of 26.8% for students ranked below the Phase 1 cutoff.

Panel B reports reduced-form RD estimates of the corresponding discontinuity in the probability of accepting a program's offer. Consistent with an early-offer effect, the results indicate that the probability of accepting a program's offer increases significantly at the cutoff, by 6.2 to 7.0 percentage points from a baseline of 25.8% for students ranked below the Phase 1 cutoff.

Panel C reports RD IV estimates of the impact of receiving an early offer from a program on the probability of ultimately accepting that program, where the estimand of interest is the ratio between the estimand from the reduced-form equation (discontinuity in acceptance probability) and the estimand from the first-stage equation (discontinuity in the early-offer probability). The results indicate that receiving an early offer from a program significantly increases the probability of accepting that program's offer by 8.2 to 9.1 percentage points. These RD estimates are remarkably similar to those we obtain using the conditional logit model: in our preferred specification (Table 3, column 5), an early offer is estimated to increase the acceptance probability by 8.7 percentage points.

[A.2]The reason why the density exhibits a spike at the Phase 1 cutoff is that we pool together all program quotas and center their cutoffs. Some program quotas have many students ranked above and below the Phase 1 cutoff whereas others have few.

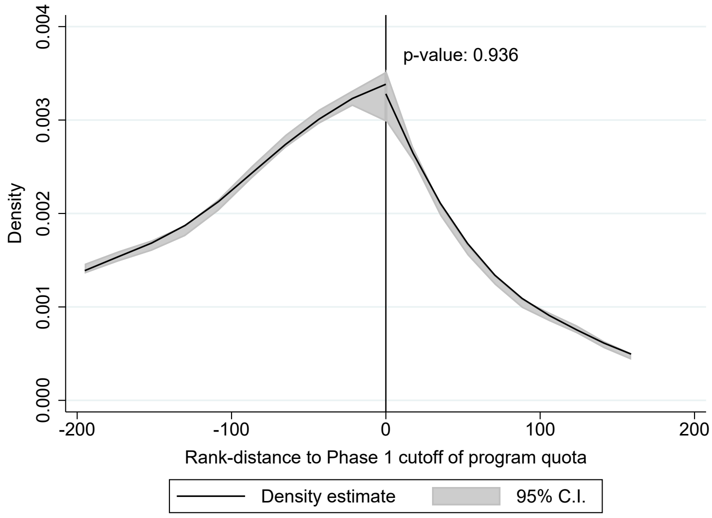

Figure C1 – Phase 1 Cutoff: Density Test

Notes: This figure implements a manipulation testing procedure using the local polynomial density estimators described in Cattaneo, Jansson and Ma (2020) (Stata command `rddensity`). The solid line indicates the density estimate and the shaded area shows the 95% confidence interval. The program quotas considered are those under which offers were made in both Phase 1 and Phase 2, with at least 10 students ranked above the Phase 1 cutoff rank and at least 10 students ranked below the Phase 1 cutoff and above the Phase 2 cutoff. The sample consists of all students who applied to at least two feasible programs and whose rank under one of the selected program quotas was above the quota's Phase 2 cutoff.

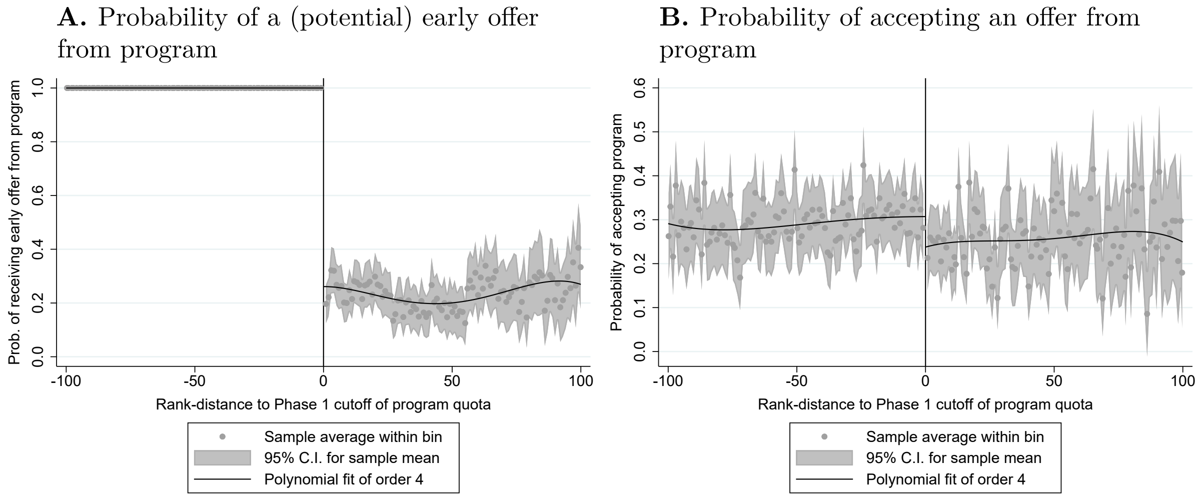

Figure C2 – Probability of Receiving and Accepting an Early Offer at a Program's Phase 1 Cutoff

Notes: This figure shows the probability of receiving a (potential) early offer (Panel A) and the probability of accepting an offer (Panel B) from a program as a function of the student's rank-distance to the Phase 1 cutoff of one of the program's quotas. The Phase 1 cutoff is the rank of the last student who received an early offer from the program under the considered quota in Phase 1. We restrict program quotas to those under which offers were made in both Phase 1 and Phase 2, with at least 10 students ranked above the Phase 1 cutoff rank and at least 10 students ranked below the Phase 1 cutoff and above the Phase 2 cutoff. The sample pools together all students who applied to at least two feasible programs and whose rank under one of the considered program quotas was above the quota's Phase 2 cutoff. Following de Chaisemartin and Behaghel (2020), the last student to receive an early offer under any program quota is removed. The plots are obtained using the Stata command `rdplot` described in Calonico et al. (2017). The dots represent early-offer probabilities (Panel A) and acceptance probabilities (Panel B) averaged within bins. The bins are selected to balance squared-bias and variance so that the integrated mean squared error is approximately minimized. The solid lines represent kernel-weighted fourth-order polynomial fits using a uniform kernel. The shaded area represents the 95% confidence intervals for local means within each bin.

Table C1 – Impact of (Potential) Early Offers on Acceptance Probability: RD Estimates

	(1)	(2)	(3)	(4)
A. First Stage: Discontinuity in probability of (potential) early offer from program				
$\mathbb{1}\{\text{Rank} \leqslant \text{Phase 1 cutoff}\}$	0.764***	0.762***	0.762***	0.763***
	(0.009)	(0.010)	(0.008)	(0.009)
Baseline mean (Rank > Phase 1 cutoff)	0.268	0.268	0.268	0.268
B. Reduced Form: Discontinuity in probability of accepting a program's offer				
$\mathbb{1}\{\text{Rank} \leqslant \text{Phase 1 cutoff}\}$	0.066***	0.070***	0.062***	0.066***
	(0.012)	(0.014)	(0.012)	(0.013)
Baseline mean (Rank > Phase 1 cutoff)	0.258	0.258	0.258	0.258
C. RD IV: Impact of early offer on acceptance probability				
EarlyOffer	0.086***	0.091***	0.082***	0.087***
	(0.016)	(0.018)	(0.016)	(0.017)
Number of observations	40,103	40,103	40,103	40,103
Number of students	19,659	19,659	19,659	19,659
RD estimation method	Conventional	Bias-corrected	Conventional	Bias-corrected
Bandwidth (rank-distance to Phase 1 cutoff)	±124.5	±124.5	±125.7	±125.7
Spline	Linear	Linear	Linear	Linear
Program-quota fixed effects (208)	No	No	Yes	Yes

Notes: Panel A reports the first-stage RD estimates of the discontinuity in the probability of a (potential) offer from a program when crossing the Phase 1 cutoff of a program's quota. The Phase 1 cutoff of a program quota is the rank of the last student who received an early offer from the program under that quota in Phase 1. Panel B reports the reduced-form RD estimates of the corresponding discontinuity in the probability of accepting a program's offer. Panel C reports the RD IV estimates of the impact of an early offer from a program on the probability of accepting the program's offer. The program quotas considered in the analysis are those under which offers were made in both Phase 1 and Phase 2, with at least 10 students ranked above the Phase 1 cutoff rank and at least 10 students ranked below the Phase 1 cutoff and above the Phase 2 cutoff. The sample pools together all students who applied to at least two feasible programs and whose rank under one of the considered program quotas was above the quota's Phase 2 cutoff. Following de Chaisemartin and Behaghel (2020), the last student to receive an early offer under any program quota is removed. The estimates are obtained using the `rdrobust` package described in Calonico et al. (2017). The specifications in columns 1 and 2 do not include covariates whereas those in columns 3 and 4 include program-quota fixed effects. Columns 1 and 3 use the mean-squared-error-optimal bandwidth following Imbens and Kalyanaraman (2012). Columns 2 and 4 in addition report bias-corrected estimates and robust standard errors following Calonico, Cattaneo and Titiunik (2014). Standard errors are clustered at the student level using the nearest neighbor variance estimation method described in the same study. ***: p <0.01.

D Additional Definitions, Proofs, and Results

This appendix first defines the Gale-Shapley algorithm (Section D.1). Then, it provides additional results and proofs for Section 4 in the main text. Specifically, Section D.2 considers a special case in which the student knows her own ordinal preferences, an assumption that is often imposed in the matching literature. Under this assumption, we show that there are no early-offer effects. Section D.3 provides an example in which the early-offer effect on offer acceptance is negative.

Section D.4 proves that the sequence of optimal strategies under the M-DA can be summarized into one strategy. Thus, it provides a theoretical foundation for Section 4.2.2 in the main text. Section D.5 proves Proposition 1.

D.1 The Gale-Shapley Algorithm

We distinguish between a "mechanism" and an "algorithm," although the literature often uses them interchangeably. Let us consider the case that students apply to university programs and that each program admits students. In our setting, a university-admissions mechanism, such as the M-DA, is a complete procedure that specifies how students and programs exchange information with the mechanism and how a matching outcome is determined. In contrast, an algorithm is a computer code that takes as inputs information from applicants and programs and delivers a matching outcome; importantly, it is silent on how relevant information is collected. Therefore, an algorithm is always one of the multiple components of a mechanism.

The Gale-Shapley algorithm can be either student-proposing or program-proposing. We focus on the latter. Specifically, taking as inputs program capacities, the programs' ranking over applicants, and students' rank-order lists of programs (ROLs), it proceeds as follows:

Round 1. Every program with capacity q_j and n_j^1 applicants extends an admission offer to its top-min$\{q_j, n_j^1\}$ applicants in its ranking over applicants. Each student who receives multiple offers keeps the highest-ranked offer according to her ROL and rejects the rest.

Generally, in:

Round ($r > 1$). Every program with $m_j^{(r-1)}$ of its previous offers rejected in round $r-1$ and n_j^r applicants who have never received its offer extends offers to the top-min$\{m_j^{(r-1)}, n_j^r\}$ applicants among those who have not received its offer. Each student who has multiple offers keeps the highest ranked offer according to her ROL and rejects the rest.

The process terminates after any round r in which no offers are rejected by students. Each program is then matched with the students that are currently holding its offer.

D.2 Ordinally Informed Student

We now investigate if the early-offer effect in Section 2 can emerge when we impose the following assumption that is common in the matching literature: agents know their own ordinal preferences (Roth and Sotomayor, 1990; Bogomolnaia and Moulin, 2001).

We call the student *ordinally informed* if the distribution of X_j, G_j, is such that with probability one, (i) either $u(X_j) > u(X_{j'})$ or $u(X_j) < u(X_{j'})$ for any $j \neq j'$, and (ii) either $u(X_j) > 0$ or $u(X_j) < 0$ for any j. In other words, the student knows her ordinal preferences and whether a program is (ex post) acceptable without any further learning. Importantly, this assumption includes the following as a special case: there is no uncertainty about program quality and there are no ties in the student's cardinal preferences.

Proposition D1. *If the student is ordinally informed, she does not learn about program quality and submits the same ROL for all O, p^0, and c under the DA, the M-DA, or the BM-DA. Her expected utility is constant across the mechanisms.*

This proposition is straightforward, and we therefore only sketch the proof here. Since the optimal strategy for the student is to submit an ROL respecting her true ordinal preferences, which are known to her without additional learning, the marginal benefit of learning more about the programs is zero under any mechanism. Since her submitted ROL is constant across mechanisms, her expected utility is constant.

Proposition D1 also leads to the following corollary.

Corollary D1. *If the student is ordinally informed, for all O, p^0, and c, there is no early-offer effect on offer acceptance under the M-DA.*

In contrast to Corollary D1, our empirical study documents a sizable early-offer effect on offer acceptance; it therefore implies that students being ordinally informed may not be plausible in our empirical setting.

D.3 Ambiguous Effects of Early Offers on Offer Acceptance

Our empirical analysis finds that an early offer increases the probability that the offer is accepted. This result does not hold in some cases. Below, we provide an example in which an early offer from a program reduces the likelihood that the offer is accepted on average; moreover, there is no first-early-offer effect. One of the key features of this example is that the student never has any incentives to learn about one of the two programs.

Suppose that the student is risk neutral and applies to two programs, $j = 1, 2$. The offer probabilities (as seen in period 0) are p_1^0 and p_2^0, while $0 < p_1^0 < p_2^0 < 1$. The distribution of X_1 is *Uniform*$(\mu_1 - \delta, \mu_1 + \delta)$ with $\mu_1 \in (1/2, 1)$; importantly, $0 < \delta < c/2$ and thus it never pays to learn about X_1. Moreover, $X_2 \sim$ *Uniform*$(0, 1)$, and there is an outside option whose value is zero.

When there is no learning, the student submits ROL 1–2 (the first choice is program 1 and the second choice is program 2) with an expected payoff $V_0(p_1, p_2) = p_1\mu_1 + (1-p_1)p_2/2$, for $p_1 \in \{p_1^0, 1\}$ and $p_2 \in \{p_2^0, 1\}$. If the student learns X_2, the expected payoff is:

$$\begin{aligned} V_1(p_1, p_2) = &\int_{\mu_1}^{1} (p_2 x_2 + (1-p_2)p_1\mu_1) dx_2 + \int_0^{\mu_1} (p_1\mu_1 + (1-p_1)p_2 x_2) dx_2 - c \\ =&V_0(p_1, p_2) + \frac{p_1 p_2}{2}(1-\mu_1)^2 - c. \end{aligned}$$

Suppose that c is such that $\frac{p_1^0}{2}(1-\mu_1)^2 < c < \frac{p_2^0}{2}(1-\mu_1)^2$. Therefore, when there is no early offer or only one early offer from program 2, the student will not learn about X_2 and thus will always submit ROL 1–2.

When the student receives only one early offer from program 1, she will learn about X_2 and ex ante (before learning) submit ROL 1–2 with probability μ_1. When there are two early offers, regardless of the arrival order, the student's learning and ranking behaviors are the same as when she receives an early offer from program 1.

We calculate the early-offer effects as follows (similar to Result 2):

$$\Pr(\text{top rank univ. 1} \mid \text{early offer from 1}) - \Pr(\text{top rank univ. 1} \mid \text{no early offer}) = \mu_1 - 1,$$
$$\Pr(\text{top rank univ. 1} \mid \text{two early offers}) - \Pr(\text{top rank univ. 1} \mid \text{early offer from 2}) = \mu_1 - 1,$$
$$\Pr(\text{top rank univ. 2} \mid \text{early offer from 2}) - \Pr(\text{top rank univ. 2} \mid \text{no early offer}) = 0,$$
$$\Pr(\text{top rank univ. 2} \mid \text{two early offers}) - \Pr(\text{top rank univ. 2} \mid \text{early offer from 1}) = 0.$$

If early offers arrive randomly, the average early-offer effect on offer acceptance is a weighted average of the above four effects, while each weight is strictly positive. Thus, it leads to a negative average effect.

We also calculate the first-early-offer effects as follows (similar to Result 3):

$$\Pr(\text{top rank univ. 1} \mid \text{offers from 1 then 2}) - \Pr(\text{top rank univ. 1} \mid \text{offers from 2 then 1}) = 0,$$
$$\Pr(\text{top rank univ. 2} \mid \text{offers from 2 then 1}) - \Pr(\text{top rank univ. 1} \mid \text{offers from 1 then 2}) = 0.$$

Therefore, there is no first-early-offer effect.

D.4 Optimal Learning Strategy under the M-DA

Recall that $\underline{t} = \min\{\min\{O\}, J\}$. In each period $t = \underline{t}, \ldots, J$, given $p^t(O)$, the student has a myopic strategy, $\psi^t(\cdot, \cdot \mid p^t(O))$, leading to (subjective) expected utility $V^t(\mathcal{U}^{(t-1)}, l^{(t-1)}, p^t(O) \mid \psi^t(\cdot, \cdot \mid p^t(O)))$, where $\mathcal{U}^{(t-1)}$ and $l^{(t-1)}$ are the learning outcomes at the end of period $(t-1)$ with $\mathcal{U}^{(\underline{t}-1)} = \mathcal{J}$ and $l^{(\underline{t}-1)} = \varnothing$. Hence, $\psi^t \in \arg\max_{\psi} V^t(\mathcal{U}^{(t-1)}, l^{(t-1)}, p^t(O) \mid \psi)$, for $t = \underline{t}, \ldots, J$. Below, we show that this sequence of strategies is equivalent to one single strategy.

Suppose that the student adopts the sequence of strategies $\{\psi^t\}_{t=\underline{t}}^J$. In a given period t, only ψ^t is applied, and at the end of the period, the student must reach a state, $(\mathcal{U}, l)$, such that $\psi^t(\mathcal{U}, l \mid p^t(O)) = 0$ (i.e., the student stops learning).

We say that a state $(\mathcal{U}, l)$ that is not $(\mathcal{J}, \varnothing)$ is *never reached* in period $\underline{t}$ if there is no learning sequence, $\{j_1, ..., j_n\} = \overline{\mathcal{U}} = \mathcal{J} \backslash \mathcal{U}$ and $\{(j_1, x_{j_1}), \ldots, (j_n, x_{j_n})\} = l$, such that $\psi^{\underline{t}}(\mathcal{J}, \varnothing \mid p^t(O)) = j_1$ and $\psi^{\underline{t}}(\mathcal{J} \backslash \{j_1, \ldots, j_m\}, \{(j_1, x_{j_1}), \ldots, (j_m, x_{j_m})\}) = j_{m+1}$ for $m = 1, \ldots, n-1$. Let $\mathcal{NR}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J)$ be the collection of states that are never reached in period $\underline{t}$ given $\{\psi^t\}_{t=\underline{t}}^J$. We can sequentially define $\mathcal{NR}(t, \{\psi^t\}_{t=\underline{t}}^J)$ for $t = \underline{t}+1, \ldots, J$.

For a state that is never reached in a period, a strategy can prescribe an arbitrary action without affecting the student's payoff. We impose a no-learning assumption on such off-equilibrium paths:

Assumption D1. *The student's strategy does not require her to learn anything in a never reached state, i.e.,* $\psi^t(\mathcal{U}, l \mid p^t(O)) = 0$ *if* $(\mathcal{U}, l) \in \mathcal{NR}(t, \{\psi^t\}_{t=\underline{t}}^J)$.

Further, we let $\mathcal{T}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J)$ be the collection of terminal states that can be reached *at the end* of period $\underline{t}$, such that $\psi^{\underline{t}}(\mathcal{U}, l \mid p^{\underline{t}}(O)) = 0$, $\forall (\mathcal{U}, l) \in \mathcal{T}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J)$. It must be that $\mathcal{T}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J) \cap \mathcal{NR}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J) = \varnothing$.

We can sequentially define $\mathcal{T}(t, \{\psi^t\}_{t=\underline{t}}^J)$ for $t = \underline{t}+1, \ldots, J$ by noting that a possible initial state in period t must be in $\mathcal{T}(t-1, \{\psi^t\}_{t=\underline{t}}^J)$.

Lemma D1. *Under Assumption D1, for any* $(\mathcal{U}, l)$, *if* $\psi^t(\mathcal{U}, l \mid p^t(O)) \neq 0$ *for some* $t \geqslant \underline{t}$, *then* $\psi^{t'}(\mathcal{U}, l \mid p^{t'}(O)) = 0$ *for all* $t' \in \{\underline{t}, \ldots, J\} \backslash \{t\}$.

Proof. Suppose that $\psi^t(\mathcal{U}, l \mid p^t(O)) \neq 0$ for some $t \geqslant \underline{t}$.

First, we consider $t = \underline{t}$. With the off-equilibrium restriction in Assumption D1 and $\psi^t(\mathcal{U}, l \mid p^t(O))$ being a pure strategy, $\psi^t(\mathcal{U}, l \mid p^t(O)) \neq 0$ implies that there exists a unique learning sequence, $\{j_1, ..., j_n\} = \overline{\mathcal{U}} = \mathcal{J} \backslash \mathcal{U}$ and $\{(j_1, x_{j_1}), \ldots, (j_n, x_{j_n})\} = l$, such that $\psi^{\underline{t}}(\mathcal{J}, \varnothing \mid p^t(O)) = j_1$ and $\psi^{\underline{t}}(\mathcal{J} \backslash \{j_1, \ldots, j_m\}, \{(j_1, x_{j_1}), \ldots, (j_m, x_{j_m})\}) = j_{m+1}$ for $m = 1, \ldots, n-1$. Uniqueness is because we consider pure strategies. Moreover, $(\mathcal{U}, l) \notin \mathcal{T}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J)$; that is, $(\mathcal{U}, l)$ is not a possible terminal state in period $\underline{t}$. This means that $(\mathcal{U}, l) \in \mathcal{NR}(t', \{\psi^t\}_{t=\underline{t}}^J)$ for $t' > \underline{t}$ and thus $\psi^{t'}(\mathcal{U}, l \mid p^{t'}(O)) = 0$ (by the off-equilibrium restriction).

Second, a similar argument can be made for $t = \underline{t}+1$. We note the following observation: $\psi^t(\mathcal{U}, l \mid p^t(O)) \neq 0$ implies that there exists a unique state $(\mathcal{U}^{(t-1)}, l^{(t-1)}) \in \mathcal{T}(t-1, \{\psi^t\}_{t=\underline{t}}^J)$ and a unique learning sequence $\{j_1, ..., j_n\} = \mathcal{U}^{(t-1)} \backslash \mathcal{U}$ and $\{(j_1, x_{j_1}), \ldots, (j_n, x_{j_n})\} = l \backslash l^{(t-1)}$ such that $\psi^t(\mathcal{U}^{(t-1)}, l^{(t-1)} \mid p^t(O)) = j_1$ and, for $m = 1, \ldots, n-1$,

$$\psi^t\left(\mathcal{U}^{(t-1)} \backslash \{j_1, \ldots, j_m\}, l^{(t-1)} \cup \{(j_1, x_{j_1}), \ldots, (j_m, x_{j_m})\}\right) = j_{m+1}.$$

Therefore, $(\mathcal{U}, l)$ is either in $\mathcal{NR}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J)$ or $\mathcal{T}(\underline{t}, \{\psi^t\}_{t=\underline{t}}^J)$, and thus $\psi^{\underline{t}}(\mathcal{U}, l \mid p^{\underline{t}}(O)) = 0$. Moreover, $(\mathcal{U}, l) \in \mathcal{NR}(t', \{\psi^t\}_{t=\underline{t}}^J)$ for $t' > \underline{t}$ and thus $\psi^{t'}(\mathcal{U}, l \mid p^{t'}(O)) = 0$.

By continuing this argument, we can show that if $\psi^t(\mathcal{U}, l \mid p^t(O)) \neq 0$ for $t \geqslant \underline{t}$, then $\psi^{t'}(\mathcal{U}, l \mid p^{t'}(O)) = 0$ for all $t' \in \{\underline{t}, \ldots, J\} \backslash \{t\}$. ■

By Lemma D1, we can define a single strategy that is equivalent to applying $\{\psi^t\}_{t=\underline{t}}^J$ sequentially, as we do in Section 4.2.2.

D.5 Proof of Proposition 1

Proof. The weak inequalities in part (i) are implied by the fact that $\psi^B(\cdot, \cdot \mid p^J(O)) \in \arg\max_\psi V(\mathcal{J}, \varnothing, p^J(O) \mid \psi)$ under the BM-DA, while $\psi^{DA}(\cdot, \cdot \mid p^0)$ and $\psi^M(\cdot, \cdot \mid p^J(O))$ may not maximize $V(\mathcal{J}, \varnothing, p^J(O) \mid \psi)$.

Furthermore, Result 4 in Section 4.3 gives an example of $(\mathcal{J}, p^0, O, F, c)$ such that the dominance of the BM-DA is strict.

For part (ii), we notice that the BM-DA and the M-DA are equivalent when there is only one early offer (i.e., there is a unique program j such that $O_j < J+1$ and $O_{j'} = J+1$ if $j' \neq j$). In this case, the M-DA achieves a higher expected utility than the DA, as implied by part (i). The opposite can be true in cases where the M-DA is not equivalent to the BM-DA. Result 4 in Section 4.3 gives a concrete example. ■

E Simulation-Based Comparison of Mechanisms

This appendix describes the simulations we carry out to compare the welfare properties of the three mechanisms studied in Section 4 in the main text: the DA, the M-DA, and the BM-DA. In keeping with our theoretical model whenever possible, we construct a stylized, closed market in which student behavior can be simulated under each mechanism using our empirical estimates based on the DoSV data, which makes it possible to compare the welfare properties of these mechanisms.

E.1 Setup

We use the same data set as for the main empirical analysis, namely the data from the DoSV procedure for 2015–16, to construct a market in which students are matched with university programs under the DA, M-DA, and BM-DA mechanisms.

E.1.1 The Market

Students. As in the main empirical analysis, we use the set of 21,711 students who applied to at least two feasible programs and accepted an offer.

Students' applications and programs. Throughout the simulations, we keep fixed the set of programs that each student i applies to, which we denote by $\mathcal{A}_i$. This set includes an outside option as well as all programs that are in the student's initial rank-order list (ROL) in the DoSV procedure for 2015–16. Introducing this outside option accounts for the possibility that participants may have applied to programs outside the platform and devoted some time learning about them. Since all students in our sample accepted an offer from the platform, we make the simplifying assumption that this outside option is never feasible. We denote by $A_i \equiv |\mathcal{A}_i|$ the number of programs in $\mathcal{A}_i$ including the outside option.

The union of $\mathcal{A}_i$ across all students in the simulation, $\bigcup_i \mathcal{A}_i$, is the set of programs in the simulated market. In total, there are 376 programs.

Program capacities. For each program j, the number of available seats, denoted by q_j, is set equal to the number of students in the simulation sample who accepted an offer from the program in reality.

Programs' ranking over students. To simplify the analysis, we depart from the German setting by imposing that each program ranks its applicants under a single ranking (instead of the multiple-quota system). We generate the programs' rankings on the basis of a student-program-specific priority score, denoted $score_{i,j}$ (higher is better), which is the average of the student's *Abitur* percentile rank and a program-specific random component:

$$score_{i,j} = \frac{Abitur_i + \nu_{i,j}}{2}, \quad \forall i, j, \tag{A.1}$$

where $Abitur_i$ represents student i's *Abitur* percentile rank (between zero and one) and $\nu_{i,j} \sim Uniform(0, 1)$.

To ensure that our analyses are performed on a subset of programs for which student preferences can be estimated, while allowing for some variation in feasible sets across simulations, we put some restrictions on the programs that can ever be feasible to a student. We define an *extended feasible set* for each student. It includes the programs in $\mathcal{A}_i$ that were ex post feasible to the student in reality and the infeasible program in $\mathcal{A}_i$ (if any) that was the closest to being feasible under the most favorable quota to the student. In the simulations, a student who applies to programs outside of this extended feasible set is considered unacceptable to the corresponding programs (i.e., she never receives offers from those programs).

E.1.2 Timeline under the Three Mechanisms

We assume that the following components are constant across the three mechanisms: (i) each student always applies to the same subset of programs in $\mathcal{A}_i$; (ii) the programs' capacities; and (iii) the programs' rankings over students.

As described in Section 4, the three mechanisms differ in terms of the existence and timing of early offers as well as the timing for students to submit their ROL.

DA. Students submit their ROL without having received early offers. The matching is determined by the program-proposing Gale-Shapley (GS) algorithm, using as inputs the students' submitted ROLs, the programs' rankings of students, and the programs' capacities.

M-DA. Each program sends out a single batch of early offers to its highest-ranked applicants up to its capacity. We assume that early offers are sent out on different dates and that the order of offer arrival is random for every student. Students are required to submit an ROL of programs after all early offers have been sent out. The matching is then determined by the program-proposing GS algorithm.

BM-DA. The timing is the same as under the M-DA mechanism, except that all early offers are sent out to students on the same date.

E.2 Learning, Rank-Order Lists, and Matching Outcome

Students' preferences, their learning behavior under the three mechanisms, and the determination of their submitted ROL and matching outcome are simulated using a model whose parameters are estimated based on the DoSV data.

E.2.1 Utility under Full Information and No Information

As in Section 4, a student's preferences over programs are unknown and can only be learned at a cost. Student i's true utility from program j (i.e., conditional on having learned her preferences for this program) is denoted by $U_{i,j}^{\text{FullInfo}}$, while $U_{i,j}^{\text{NoInfo}}$ denotes her expected—or perceived—utility without learning.

Utility under full information. Student i's utility from program j under full information, $U_{i,j}^{\text{FullInfo}}$, takes the following form:

$$U_{i,j}^{\text{FullInfo}} = V_{i,j}^{\text{FullInfo}} + \epsilon_{i,j}^{\text{FullInfo}}, \quad \forall i, j \in \mathcal{A}_i, \tag{A.2}$$

where $V_{i,j}^{\text{FullInfo}}$ represents the deterministic component of the student's utility, which depends on observable student-program-specific characteristics (e.g., field of study and distance), and $\epsilon_{i,j}^{\text{FullInfo}}$ represents the (random) idiosyncratic component, which is unobserved and i.i.d. type I extreme value (Gumbel) distributed.

To quantify $V_{i,j}^{\text{FullInfo}}$, we rely on the same sample as in the main empirical analysis of the early-offer effect, i.e., those students who applied to at least two feasible programs and accepted an offer. Under the assumption that a student always learns her preference for the program from which she has received her first early offer, $V_{i,j}^{\text{FullInfo}}$ is calculated by assuming that i receives her first early offer from program j.

We use students' final ROLs. After restricting each student's choice set to the ex post feasible programs that she included in her initial ROL, we estimate the following specification using a rank-ordered logit to extract information from students' final ROLs as described in Section 2.3:

$$\begin{aligned} U_{i,j} &= V_{i,j}(\boldsymbol{X}_{i,j}, \boldsymbol{W}_{i,j}, EO_{i,j}, FEO_{i,j}) + \eta_{i,j} \\ &= \boldsymbol{X}_{i,j}\beta + \delta_1\, EO_{i,j} + \delta_2\, FEO_{i,j} + (EO_{i,j} \cdot \boldsymbol{W}_{i,j})\gamma_1 + (FEO_{i,j} \cdot \boldsymbol{W}_{i,j})\gamma_2 + \eta_{i,j}, \quad \forall i, j, \end{aligned} \tag{A.3}$$

where $\boldsymbol{X}_{i,j}$ and $\boldsymbol{W}_{i,j}$ are row vectors of student-program-specific characteristics; $\boldsymbol{X}_{i,j}$ includes program fixed effects, distance, distance squared, and a dummy for whether the program is in the student's region (*Land*); $\boldsymbol{W}_{i,j}$ includes university fixed effects, field-of-study fixed effects,[A.3] distance, distance squared, and a dummy for whether the program is in the student's region; $EO_{i,j}$ is an indicator for whether student i has received an early offer from program j; $FEO_{i,j}$ is an indicator for whether the first early offer received by student i was from program j; and $\eta_{i,j}$ is a type I extreme value.

In this specification, the coefficients γ_1 and γ_2 on the interaction terms between the indicators for early offer/first early offer and the student-program-specific characteristics $\boldsymbol{W}_{i,j}$ capture indirectly the learning effects induced by early offers. They measure how early offers modify the weights that students place on the observable characteristics of the programs from which they received such offers.

We then compute $V_{i,j}^{\text{FullInfo}}$ as follows:

$$\begin{aligned} V_{i,j}^{\text{FullInfo}} &= \widehat{V}_{i,j}(\boldsymbol{X}_{i,j}, \boldsymbol{W}_{i,j}, EO_{i,j} = 1, FEO_{i,j} = 1) \\ &= \boldsymbol{Z}_{i,j}\widehat{\beta} + \widehat{\delta}_1 + \widehat{\delta}_2 + \boldsymbol{W}_{i,j}(\widehat{\gamma}_1 + \widehat{\gamma}_2), \quad \forall i, j, \end{aligned} \tag{A.4}$$

where $(\widehat{\beta}, \widehat{\delta}_1, \widehat{\delta}_2, \widehat{\gamma}_1, \widehat{\gamma}_2)$ are the parameter estimates from Equation (A.3).

Utility under no information. Similar to $U_{i,j}^{\text{FullInfo}}$, we assume that student i's utility from program j without learning, $U_{i,j}^{\text{NoInfo}}$, takes the following form:

$$U_{i,j}^{\text{NoInfo}} = V_{i,j}^{\text{NoInfo}} + \epsilon_{i,j}^{\text{NoInfo}}, \quad \forall i, j \in \mathcal{A}_i, \tag{A.5}$$

where $V_{i,j}^{\text{NoInfo}}$ and $\epsilon_{i,j}^{\text{NoInfo}}$ are the deterministic and idiosyncratic components, respectively; $\epsilon_{i,j}^{\text{NoInfo}}$ is assumed to be i.i.d. type I extreme value distributed and $\epsilon_{i,j}^{\text{NoInfo}} \perp \epsilon_{i,j}^{\text{FullInfo}}$.

We further assume that $V_{i,j}^{\text{NoInfo}}$ is drawn from a normal distribution centered at

[A.3] The programs are grouped into 12 fields of study (architecture and design, business and economics, engineering, language and culture, law, mathematics and computer science, medicine, natural sciences, psychology, social sciences, social work, and teaching programs) and a residual group for other fields.

$V_{i,j}^{\text{FullInfo}}$:

$$V_{i,j}^{\text{NoInfo}} \sim N\left(V_{i,j}^{\text{FullInfo}}, \left(\text{s.e.}(V_{i,j}^{\text{FullInfo}})\right)^2\right), \quad \forall i, j \in \mathcal{A}_i, \tag{A.6}$$

where s.e.($V_{i,j}^{\text{FullInfo}}$) is the standard error of the predicted value in Equation (A.4).

E.2.2 Preference Discovery under the Three Mechanisms

As in Section 4, for each mechanism, we assume that the learning technology is such that a student either learns her true utility from program j, $U_{i,j}^{\text{FullInfo}}$, or learns nothing beyond $U_{i,j}^{\text{NoInfo}}$. We denote by $\lambda_{i,j}^{m}$ an indicator that takes the value of one if student i learns her true utility from program j under mechanism m, and zero otherwise.

Learning costs. We do not have an estimate of learning costs. Therefore, we impose the simplifying assumption that under any mechanism, a student learns her true preferences for half of the programs in $\mathcal{A}_i$ (which may include learning the outside option). While this assumption neglects any potential effects of a matching mechanism on the amount of learning, it allows us to ignore the learning costs when comparing welfare between mechanisms.

Learning under the DA. Under the DA mechanism, we assume that each student learns her true preferences for a random half (rounded up to the next lower integer) of the programs to which she has applied. Let $\omega_i^{\text{DA}} : \mathcal{A}_i \to \{1, 2, ..., A_i\}$ denote a function such that $\omega_i^{\text{DA}}(j)$ returns the order of program j at which it might be learned by student i. In the simulations, $\omega_i^{\text{DA}}(j)$ is chosen randomly. Student i's learning outcome for program j under the DA is:

$$\lambda_{i,j}^{\text{DA}} = \begin{cases} 1 & \text{if } \omega_i^{\text{DA}}(j) \leqslant \left\lfloor \frac{A_i}{2} \right\rfloor \\ 0 & \text{if } \omega_i^{\text{DA}}(j) > \left\lfloor \frac{A_i}{2} \right\rfloor \end{cases}, \quad \forall i, j \in \mathcal{A}_i, \tag{A.7}$$

where $\lfloor \cdot \rfloor$ represents the floor function.

Learning under the M-DA. Under the M-DA mechanism, a student may receive early offers at different dates before submitting her ROL. As in our theoretical model, an early offer may change a student's learning behavior. Compared to the DA, students' learning under the M-DA is modified by taking into account early offers and the order in which they are received.

Specifically, we assume that a student always learns her first early offer and then alternates between (i) learning a randomly chosen program from the ones in $\mathcal{A}_i$ she has not learned yet (including those from which she may later receive an early offer) and (ii) learning her early offers (if any) in the order in which they arrive. Similar to Section 4, the underlying assumption is that under the M-DA, a student's learning decision is made "myopically" period by period: each time a student receives an early offer, she learns her utility from this program (unless she has already learned her true preferences for half of the programs in $\mathcal{A}_i$); during the time interval between two consecutive early offers (or if the students has already learned her preferences for all early offers), she learns at random one of the programs that have not yet been learned.

Define $e_i : \{1, 2, \ldots, A_i\} \to \mathcal{A}_i \bigcup \varnothing$ such that student i's j^{th} early offer is from program $e_i(j)$ if $e_i(j) \neq \varnothing$ and such that i has no more than $j-1$ early offers if $e_i(j) = \varnothing$.

Further, we define $\omega_i^{\text{M-DA}} : \mathcal{A}_i \to \{1, 2, ..., A_i\}$ such that $\omega_i^{\text{M-DA}}(j)$ is the (potential) learning order of program j under the M-DA. Specifically, if the student does not receive any early offers, $\omega_i^{\text{M-DA}} = \omega_i^{\text{DA}}$. If the student receives one or more early offers, $\omega_i^{\text{M-DA}}$ is constructed in A_i steps as follows:

(1) We define L as the latest early offer and set $L = 1$. Let $\omega_i^{\text{M-DA}}(e_i(L)) = 1$, i.e., the first early offer is learned first.

(l) ($2 \leqslant l \leqslant A_i$) There are two different cases:

(a) $\omega_i^{\text{M-DA}}(e_i(L)) = l - 1$; i.e., the latest early offer, $e_i(L)$, was chosen to be learned in step $l - 1$ because it was the latest early offer then. In this case, we let $\omega_i^{\text{M-DA}}(j) = l$ where $j = \arg\min_{j' \in \mathcal{A}_i:\ \omega_i^{\text{M-DA}}(j') \notin \{1,...,l-1\}} \omega_i^{\text{DA}}(j')$. That is, the student learns in step l the earliest program, as determined by ω_i^{DA}, among those that have not been learned.

(b) $\omega_i^{\text{M-DA}}(e_i(L)) < l - 1$; i.e., the latest early offer, $e_i(L)$, was chosen to be learned in a step earlier than $l - 1$ (or, equivalently, the program learned in step $l - 1$ was not an early offer then). Let $L = L + 1$, i.e., the next early offer becomes the latest early offer. If $e_i(L) \neq \varnothing$ and $\omega_i^{\text{M-DA}}(e_i(L)) \notin \{1, \ldots, l - 1\}$, we let $\omega_i^{\text{M-DA}}(e_i(L)) = l$; otherwise, $\omega_i^{\text{M-DA}}(j) = l$ where $j = \arg\min_{j' \in \mathcal{A}_i:\ \omega_i^{\text{M-DA}}(j') \notin \{1,...,l-1\}} \omega_i^{\text{DA}}(j')$. That is, the student learns either the latest early offer (if any and if it has not been learned) or the earliest program, as determined by ω_i^{DA}, among those that have not been learned.

Student i's learning outcome for program j under the M-DA is then defined as

$$\lambda_{i,j}^{\text{M-DA}} = \begin{cases} 1 & \text{if } \omega_i^{\text{M-DA}}(j) \leqslant \left\lfloor \frac{A_i}{2} \right\rfloor \\ 0 & \text{if } \omega_i^{\text{M-DA}}(j) > \left\lfloor \frac{A_i}{2} \right\rfloor \end{cases}, \quad \forall i, j \in \mathcal{A}_i. \tag{A.8}$$

By construction, if a student does not receive early offers, her learning outcomes under the M-DA are the same as under the DA, i.e., $\lambda_{i,j}^{\text{M-DA}} = \lambda_{i,j}^{\text{DA}}$ for all $j \in \mathcal{A}_i$. We maintain such a correlation between $\lambda_{i,j}^{\text{M-DA}}$ and $\lambda_{i,j}^{\text{DA}}$ (or, equivalently, between $\omega_i^{\text{M-DA}}$ and ω_i^{DA}) so that the differences between the two mechanisms are driven only by the arrival of early offers.

Example: Suppose that $\mathcal{A}_i = \{j_1, j_2, j_3, j_4\}$ and that student i's potential learning sequence under the DA is (j_1, j_2, j_3, j_4). If the student receives early offers from three of these programs in the order (j_4, j_2, j_1), the learning sequence under the M-DA is (j_4, j_1, j_2, j_3), implying that the student first learns j_4 and then j_1.[A.4] If instead the arrival order of the early offers is (j_2, j_1, j_4), the learning sequence under the M-DA is (j_2, j_1, j_3, j_4), so the student first learns j_2 and then j_1.[A.5]

[A.4] The learning sequence under the M-DA is determined as follows: (i) the first program in the sequence is the student's first early offer, i.e., j_4; (ii) the next program is the first one in the learning sequence under the DA that has not yet been learned, i.e., j_1; (iii) then comes the second early offer (j_2), as it has not been learned in the previous step; (iv) the last program is the one in the learning sequence under the DA that has not yet been learned, i.e., j_3.

[A.5] The learning sequence under the M-DA is determined as follows: (i) the first program in the sequence is the student's first early offer, i.e., j_2; (ii) the next program is the first one in the learning sequence under the DA that has not yet been learned, i.e., j_1; (iii) since the second early offer (j_1) has been learned in the previous step, the next program to be learned is the first program in the learning sequence under the DA that has not yet been learned, i.e., j_3; (iv) the last program is the next one in the learning sequence under the DA that has not yet been learned, i.e., j_4.

Learning under the BM-DA. Under the BM-DA mechanism, each student receives her early offers on a single date before submitting her ROL. In contrast to the M-DA, we assume that a student always learns her early offers before learning other programs, up to the point where she has learned half of the programs to which she has applied.

Define $\omega_i^{\text{BM-DA}} : \mathcal{A}_i \to \{1, 2, ..., A_i\}$ such that $\omega_i^{\text{BM-DA}}(j)$ returns the (potential) learning order of program j under the BM-DA mechanism. If the student does not receive early offers, we assume that the learning order is the same as under the DA and the M-DA, i.e., $\omega_i^{\text{BM-DA}} = \omega_i^{\text{M-DA}} = \omega_i^{\text{DA}}$. If instead the student receives one or more early offers, we make the following assumptions: (i) programs that made an early offer to the student are learned before programs that did not; (ii) the relative learning order of early offers is given by ω_i^{DA}; and (iii) programs that did not extend an early offer to the student are learned in the same relative order as under the DA (as given by ω_i^{DA}).

Under the BM-DA mechanism, student i's learning outcome for program j is then defined as

$$\lambda_{i,j}^{\text{BM-DA}} = \begin{cases} 1 & \text{if } \omega_i^{\text{BM-DA}}(j) \leqslant \left\lfloor \frac{A_i}{2} \right\rfloor \\ 0 & \text{if } \omega_i^{\text{BM-DA}}(j) > \left\lfloor \frac{A_i}{2} \right\rfloor \end{cases}, \quad \forall i, j \in \mathcal{A}_i. \tag{A.9}$$

If a student does not receive early offers, her learning outcomes under the BM-DA mechanism are the same as under the DA and the M-DA, i.e., $\lambda_{i,j}^{\text{BM-DA}} = \lambda_{i,j}^{\text{DA}} = \lambda_{i,j}^{\text{M-DA}}$ for all $j \in \mathcal{A}_i$. Again, we maintain such correlations among $\lambda_{i,j}^{\text{BM-DA}}$, $\lambda_{i,j}^{\text{M-DA}}$, and $\lambda_{i,j}^{\text{DA}}$ (or, equivalently, among $\omega_i^{\text{BM-DA}}$, $\omega_i^{\text{M-DA}}$, and ω_i^{DA}) so that the differences between any two mechanisms are driven only by the arrival of early offers.

E.2.3 Determination of Submitted ROL and Matching Outcome

Perceived utility. At the time of submitting her final ROL (i.e., conditional on all her information at that time), student i's perceived utility from program j under mechanism m, $U_{i,j}^m$, depends on whether or not she has learned her preferences for that program:

$$U_{i,j}^m = \lambda_{i,j}^m \cdot U_{i,j}^{\text{FullInfo}} + (1 - \lambda_{i,j}^m) U_{i,j}^{\text{NoInfo}}, \quad \forall i, j \in \mathcal{A}_i. \tag{A.10}$$

Submitted ROL. Each student is assumed to submit a complete and truthful (w.r.t. $U_{i,j}^m$) ranking of the programs in $\mathcal{A}_i$.

Matching outcome. For each mechanism, the program-proposing GS algorithm is used to match the students and programs. We assume that after the matching takes place, students always experience their true preference for the program to which they have been matched. A student's utility of her matching outcome, $\mu(i)$, can therefore be evaluated at $U_{i,\mu(i)}^{\text{FullInfo}}$.

E.3 Monte Carlo Simulations

The simulations are performed among the same S Monte Carlo samples under each of the three mechanisms. We set S =10,000.

E.3.1 Components Fixed across Simulation Samples

Across the simulation samples, the following components are held fixed as specified in Section E.1.1:

Market participants. Student characteristics and program attributes are fixed. The set of students is $\mathcal{I} \equiv \{1, ..., I\}$ while the set of programs is $\mathcal{J} \equiv \{1, \ldots, J\}$. In the simulations, I =21,711 and J=376.

Student Applications. Each student i applies to all programs in $\mathcal{A}_i$. On average, students in the simulation sample apply to 5.7 programs (including the outside option).

Program capacities. The programs' capacities are $\{q_j\}_{j=1}^{J}$.

Programs' rankings of students. Each program ranks its applicants based on the student-program specific score defined by Equation (A.1). If the program does not belong to the student's extended feasible set as defined in Section E.1.1, the student is assumed to be unacceptable to the program.

Early offers. Under the M-DA and BM-DA mechanisms, early offers are made to each program's top-ranked applicants up to the program's capacity. The set of early offers is the same under both mechanisms.

Utility under full information. For each student i and program $j \in \mathcal{A}_i$, the deterministic component of the student's utility from the program under full information, $V_{i,j}^{\text{FullInfo}}$, is calculated using Equation (A.4) and is stored together with the standard error of the prediction, s.e.$(V_{i,j}^{\text{FullInfo}})$.

E.3.2 Simulation Steps

Other than those in Section E.3.1, a component in general is independently drawn in each simulation sample. This includes idiosyncratic utility shocks, utility without learning, early offer arrival orders, and potential learning orders. Note that in a given simulation sample, we have the same market for each of the three mechanisms.

The S independent Monte Carlo samples are generated as follows:

Step 1: Utility functions with and without learning. Let $U_{i,j,s}^{\text{FullInfo}}$ denote student i's utility from program j in sample s under full information and $U_{i,j,s}^{\text{NoInfo}}$ her utility without learning. For each student i in sample s:

(i) Draw a set of i.i.d. type I extreme values $\epsilon_{i,j,s}^{\text{FullInfo}}$ and $\epsilon_{i,j,s}^{\text{NoInfo}}$ for all $j \in \mathcal{A}_i$.

(ii) Use Equation (A.2) to compute the student's true utility from program j in sample s, $U_{i,j,s}^{\text{FullInfo}}$:

$$U_{i,j,s}^{\text{FullInfo}} = V_{i,j}^{\text{FullInfo}} + \epsilon_{i,j,s}^{\text{FullInfo}}, \quad \forall i, j \in \mathcal{A}_i.$$

Note that $V_{i,j}^{\text{FullInfo}}$ is constant across simulation samples.

(ii) Use Equation (A.5) to compute the student's utility from program j in sample s without learning, $U_{i,j,s}^{\text{NoInfo}}$:

$$U_{i,j,s}^{\text{NoInfo}} = V_{i,j,s}^{\text{NoInfo}} + \epsilon_{i,j,s}^{\text{NoInfo}}, \quad \forall i, j \in \mathcal{A}_i,$$

where $V_{i,j,s}^{\text{NoInfo}} \sim N\big(V_{i,j}^{\text{FullInfo}}, \big(\text{s.e.}(V_{i,j}^{\text{FullInfo}})\big)^2\big)$ as specified in Equation (A.6).

Step 2: Early offer arrival and learning order. For each student i in sample s:

(i) Draw an arrival order $e_{i,s}$ of i's early offers under the M-DA mechanism. Recall that the set of i's early offers is fixed across simulation samples.

(ii) Generate the (potential) learning sequences $\omega_{i,s}^{\text{DA}}$, $\omega_{i,s}^{\text{M-DA}}$, and $\omega_{i,s}^{\text{BM-DA}}$ as specified in Section E.2.2.

Step 3: Learning outcomes. Let $\lambda_{i,j,s}^{m}$ be an indicator for whether student i learns her true preferences for program j in sample s under mechanism $m \in \{\text{DA, M-DA, BM-DA}\}$. The learning outcomes $\lambda_{i,j,s}^{\text{DA}}$, $\lambda_{i,j,s}^{\text{M-DA}}$, and $\lambda_{i,j,s}^{\text{BM-DA}}$ are computed from the learning sequences $\omega_{i,s}^{\text{DA}}$, $\omega_{i,s}^{\text{M-DA}}$, and $\omega_{i,s}^{\text{BM-DA}}$ as specified in Equations (A.7), (A.8), and (A.9).

Step 4: Submitted ROLs. Let $U_{i,j,s}^{m}$ denote student i's perceived utility from program j in sample s under mechanism $m \in \{\text{DA, M-DA, BM-DA}\}$. For each student i in sample s under mechanism m:

(i) Use Equation (A.10) to compute

$$U_{i,j,s}^{m} = \lambda_{i,j,s}^{m} \cdot U_{i,j,s}^{\text{FullInfo}} + (1 - \lambda_{i,j,s}^{m}) U_{i,j,s}^{\text{NoInfo}}, \quad \forall i, j \in \mathcal{A}_i.$$

(ii) Let each student submit a complete ranking of the programs in $\mathcal{A}_i$, truthful w.r.t. $U_{i,j,s}^{m}$.

Step 5: Matching. For each sample s and mechanism $m \in \{\text{DA, M-DA, BM-DA}\}$, the program-proposing GS algorithm is used to match the students and programs based on (i) students' submitted ROLs, (ii) the programs' rankings of applicants, and (iii) the programs' capacities. Note that the last two components are constant across s. Let $\mu(i, s, m)$ denote student i's match in sample s under mechanism m.

As a benchmark, we also simulate the match that would be observed under full information. Specifically, we let each student rank the programs in her ROL by $U_{i,j,s}^{\text{FullInfo}}$, and then only Step 5 is needed to be run.

E.4 Comparisons between the Mechanisms

We compare the DA, M-DA, and BM-DA mechanisms along two dimensions: students' submitted ROLs and the utility that students derive from the matching outcome.

Submitted ROLs. To contrast the different mechanisms in terms of how they affect students' preference discovery, we compare in each simulation the ROL that a student submits under each of the three mechanisms to the ROL that she would submit under full information (her "true" preferences).

Because it is payoff-irrelevant how an infeasible program is ranked, these comparisons are restricted to the programs that are ex post feasible to the student under the considered mechanism. Specifically, the ex post feasible programs are those to which the student applied that either did not fill their capacity or for which the student was ranked above the lowest-ranked student who was admitted to the program.

We compute the following statistic for each mechanism $m \in \{\text{DA, M-DA, BM-DA}\}$:

$$\theta^m \equiv \frac{1}{S \cdot I} \sum_{S=1}^{S} \sum_{i=1}^{I} \mathbb{1}\begin{pmatrix}\text{student } i\text{'s ex post feasible programs in sample } s \text{ under} \\ \text{mechanism } m \text{ are ranked in order of full info preferences}\end{pmatrix},$$

where $\mathbb{1}(\cdot)$ is an indicator function. In other words, θ^m is the fraction of students who, under mechanism m, rank ex post feasible programs in the order of their true preferences, averaged across the simulation samples.

Expected utility of students. To compare student welfare across mechanisms, we adopt an "ex ante" perspective by taking an average across the simulation samples. As detailed in Section E.3.2, sample-specific components include idiosyncratic utility shocks, utility without learning, early offer arrival orders, and potential learning sequences. As a result, a student's match may change across the samples.

Recall that each student learns her true preferences for the same number of programs under the DA, M-DA, and BM-DA mechanisms (see the discussion in Section E.2.2). Thus, learning costs can be ignored in the welfare comparison.

For each student, her expected utility is the average of the student's full-information utility of her matches across the simulation samples. We then perform pairwise comparisons of mechanisms, say between m_1 and m_2, based on the shares of students whose expected utility is (i) strictly higher under mechanism m_1 than under mechanism m_2, (ii) strictly lower, or (iii) equal.

Formally, let $U_{i,\mu(i,m,s),s}$ denote student i's utility from $\mu(i,m,s)$, her match in sample s under mechanism m. If the student is assigned to a program (i.e., $\mu(i,s,m) \neq \varnothing$), $U_{i,\mu(i,m,s),s}$ is evaluated as the student's utility from the program under full information, i.e., $U_{i,\mu(i,s,m),s} \equiv U^{\text{FullInfo}}_{i,\mu(i,s,m),s}$. If the student is unmatched (i.e., $\mu(i,s,m) = \varnothing$), we assume that her utility is below that of the least preferred program in her extended feasible set (as defined in Section E.1.1), which we denote by $\mathcal{F}_i$. Specifically, this utility is equal to the utility of the student's least preferred program in $\mathcal{F}_i$ minus the standard deviation of $\epsilon^{\text{FullInfo}}_{i,j}$:

$$U_{i,\varnothing,s} \equiv \left(\min_{j \in \mathcal{F}_i} U^{\text{FullInfo}}_{i,j,s}\right) - \frac{\pi}{\sqrt{6}}.$$

Therefore, student i's expected utility under mechanism m, denoted by EU^m_i, is:

$$\text{EU}^m_i \equiv \frac{1}{S} \sum_{s=1}^{S} U_{i,\mu(i,s,m),s}.$$

To compare students' expected utility under two mechanisms m_1 and m_2, we compute the following statistics:

(i) $\pi_{(m_1 \succ m_2)}$: Share of students whose expected utility is strictly higher under mechanism m_1 than under mechanism m_2:

$$\pi_{(m_1 \succ m_2)} \equiv \frac{1}{I} \sum_{i=1}^{I} \mathbb{1}(\mathrm{EU}_i^{m_1} > \mathrm{EU}_i^{m_2}).$$

(ii) $\pi_{(m_2 \succ m_1)}$: Share of students whose expected utility is strictly lower under mechanism m_1 than under mechanism m_2:

$$\pi_{(m_2 \succ m_1)} \equiv \frac{1}{I} \sum_{i=1}^{I} \mathbb{1}(\mathrm{EU}_i^{m_1} < \mathrm{EU}_i^{m_2}).$$

(iii) $\pi_{(m_1 \sim m_2)}$: Share of students whose expected utility is the same under both mechanisms m_1 and m_2:

$$\pi_{(m_1 \sim m_2)} \equiv \frac{1}{I} \sum_{i=1}^{I} \mathbb{1}(\mathrm{EU}_i^{m_1} = \mathrm{EU}_i^{m_2}).$$

In Section 4.4 of the main text, we use the above statistics to compare student welfare under (1) full information versus the DA, (2) the M-DA versus the DA, (3) the BM-DA versus the DA, and (4) the BM-DA versus the M-DA.

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