Decentralizing Centralized Matching Markets: Implications From Early Offers in University Admissions

Julien Grenet (Paris School of Economics)
Yinghua He (Rice University)
Dorothea Kübler (WZB Berlin Social Science Center)

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Ludwig-Maximilians-Universität München | Humboldt-Universität zu Berlin
Spokesperson: Prof. Dr. Klaus M. Schmidt, University of Munich, 80539 Munich, Germany
+49 (89) 2180 3405 | info@rationality-and-competition.de

Decentralizing Centralized Matching Markets: Implications from Early Offers in University Admissions*

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Abstract

The matching literature commonly rules out that market design itself shapes agent preferences. Underlying this premise is the assumption that agents know their own preferences at the outset and that preferences do not change throughout the matching process. Under this assumption, a centralized matching market can often outperform a decentralized one. Using a quasi-experiment in Germany's university admissions, we provide evidence against this assumption. We study a centralized clearinghouse that implements the early stages of the university-proposing Gale-Shapley deferred-acceptance mechanism in real time, resembling a decentralized market with continuous offers, rejections, and acceptances. With data on the exact timing of every decision, we show that early offers are more likely to be accepted than (potential) later offers, despite early offers not being made by more desirable universities. Furthermore, early offers are only accepted after some time rather than immediately. These results and direct survey evidence are consistent with a model of information acquisition: it is costly for students to learn about universities and accepting a university that turns out to be inferior causes regret. We discuss and rule out some alternative hypotheses. Our findings motivate a hybrid mechanism that balances centralization and decentralization. By allowing sequential learning, it improves welfare, especially in markets with substantial learning costs.

JEL Codes: C78, D47, I23, D81, D83

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*Grenet: CNRS and Paris School of Economics, 48 boulevard Jourdan, 75014 Paris, France (e-mail: julien.grenet@psemail.eu); He: Rice University and Toulouse School of Economics, Department of Economics MS-22, Houston, TX 77251 (e-mail: yinghua.he@rice.edu); Kübler: WZB Berlin Social Science Center, Reichpietschufer 50, D-10785 Berlin, Germany (e-mail: dorothea.kuebler@wzb.eu) and Technical University Berlin. For constructive comments, we thank Inácio Bó, Caterina Calsamiglia, Estelle Cantillon, Laura Doval, Tobias Gamp, Rustamdjan Hakimov, Thilo Klein, as well as seminar and conference participants at CREST/Polytechnique, Matching in Practice (2017 Brussels), Gothenburg, Stanford, and ZEW Mannheim. Jennifer Rontganger provided excellent copy editing service. The authors are grateful to the Stiftung für Hochschulzulassung, in particular Matthias Bode, for invaluable assistance in understanding the DoSV procedure. Financial support from the French National Research Agency (*Agence Nationale de la Recherche*) through project ANR-14-FRAL-0005 FDA and the German Research Foundation (*Deutsche Forschungsgemeinschaft*) through projects KU 1971/3-1 and CRC TRR 190 is gratefully acknowledged.

Research on the design of matching markets has been a success story, not least because it has resulted in improved, centralized designs for university admissions, school choice, and many entry-level labor markets (Roth and Peranson, 1999; Abdulkadiroğlu et al., 2009; Pathak, 2011). In a standard centralized market, each agent is required to rank her potential matching partners. Then a matching algorithm is run, using the rank-order lists and generating at most one match offer to an agent.[1] Centralization has been a common contributor to the success. Early examples include labor markets for medical graduates in the UK and the U.S. (Roth, 1990). Recently, centralization has deepened further as more market segments are integrated. For instance, charter and traditional public school admissions are unified in a single-offer centralized design in Denver (Abdulkadiroğlu et al., 2017) and New Orleans (Abdulkadiroğlu et al., 2017b).

This trend toward centralization is often guided by research on market design, and typically aims at fighting congestion and the unraveling of markets. By assuming that every agent knows her own preferences upon participation and has fixed preferences throughout the process, the literature identifies improved centralized designs for a market (see, for examples, Roth and Sotomayor, 1990; Abdulkadiroğlu et al., 2017a). This known-and-fixed-preferences assumption implies that market design itself, such as centralization and decentralization, has no effect on agent preferences, which is indispensable for the comparison between designs.[2]

Our paper provides unambiguous empirical evidence against the known-and-fixed-preferences assumption. In an administrative data set on university admissions in Germany, we identify a quasi-experiment in which the arrival time of admission offers is exogenous to student preferences. We show that a student is more likely to accept an early offer relative to (potential) later offers, which cannot be reconciled with the known-and-fixed-preferences assumption.

This finding is consistent with students learning about university qualities at a cost, which is corroborated by evidence from a survey of students. This learning is plausible in reality. To be able to form preferences over universities, a student must consider many

[1] In many-to-one matching such as school choice and college admissions, an agent who can accept multiple matching partners, such as a school or a college, will receive multiple match offers. However, an agent on the other side, who can accept at most one match partner, will obtain at most one offer.

[2] An exception are models with externalities such as peer effects. For example, in Calsamiglia et al. (2019), student preferences over schools depend on the composition of the post-match student body. Market design can influence who goes to which school and thereby affect student preferences.

aspects of every university, including academic quality, courses offered, and quality of life. Moreover, as more market segments are integrated in a centralized design, the number of potential matching partners can be overwhelming. Therefore, agents in practice do not enter a market endowed with known preferences over all options, and, more importantly, market design can itself influence agents' learning activities.

Our results provide novel insights for matching market design, particularly regarding the importance of balancing centralization and decentralization. In a decentralized market, an agent does not commit to a rank order over her match partners and may receive several offers over time, which facilitates learning about match qualities sequentially. By contrast, despite its numerous advantages, a standard centralized design often requires an agent to learn match qualities without knowing for sure which offers she will receive, which may lead to welfare losses. For markets with substantial learning costs, we propose a hybrid design that combines the advantages of both centralization and decentralization. This hybrid design can be implemented by an online clearinghouse and resembles some aspects of university admissions in France and Germany.

Our empirical investigation takes advantage of a unique centralized matching mechanism with features of a decentralized market. It is called DoSV, *Dialogorientiertes Serviceverfahren*, literally meaning dialogue-oriented service procedure. The mechanism is used for admissions to over-demanded university programs in Germany. Students apply to programs which transmit the applications to the clearinghouse. The procedure is based on the program-proposing deferred acceptance mechanism (DA), but differs from the standard implementation in that students can defer the commitment to their rank-order lists (ROLs) of programs. Specifically, the DoSV extends the early stages of DA and makes them dynamic. For a "decentralized" phase of 34 days, students and programs interact as if in a decentralized market. Programs make admission offers to their preferred students in real time, 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.[3] By contrast, the DA as it is commonly implemented gives a student at most one offer, since any potential offer from a lower-ranked program is automatically rejected by the algorithm on her behalf. At the end of this decentralized phase, students who have not yet accepted an

[3] In this decentralized phase, students have time to consider multiple offers since the programs extend admission offers to them, similar to the program-proposing DA. Relatedly, Bó and Hakimov (2018) describe a mechanism that also combines dynamic steps with a final DA phase but is based on the student-proposing DA.

offer are required to finalize their ROLs and to participate in the program-proposing DA. In this "centralized" phase, the mechanism is run for the remaining students and seats, assigning the seats to the students through a computerized algorithm. For a student who holds multiple offers from the decentralized phase, only the highest-ranked offer in her final ROL is kept once the algorithm starts. A student will never lose her highest-ranked offer from the decentralized phase, while in the centralized phase she may receive an offer from a program that is ranked even higher in her final ROL.

We analyze a comprehensive administrative data set that contains every event during the admission process as well as its exact timing. A program is defined as being *feasible* to a student if the student has applied to the program and would receive its admission offer if she does not exit the process 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 offers arriving in the centralized phase, an offer that arrives during the decentralized phase, which we denote as an *early offer*, is more likely to be accepted. The effect is sizable when we use distance from a student's home to the university as a "numeraire." At the sample mean of distance to programs (126 kilometers), an early offer gives the corresponding program a boost in utility equivalent to reducing the distance by 61 kilometers. The very first early offer has an even larger effect, amounting to a reduction of 79 kilometers.

Another way to gauge the magnitude of the early-offer effect is to calculate its impact on offer acceptance probability. In our sample, a feasible program is accepted, on average, by a student with a probability of 0.385. An early offer that is not the very first one increases the acceptance probability by 8.7 percentage points—a 27.9 percent increase. The very first early offer has a larger marginal effect. It increases the acceptance probability by 11.8 percentage points—a 38.3 percent increase.

This positive early-offer effect is not due to early offers coming from programs that are more over-demanded or that accept higher-ability students. Moreover, early offers are not from programs that are ranked higher in students' initial ROLs, and programs are not aware of the students' ROLs throughout the process. Programs can start making their offers at any point in time within one month, and subsequent offers are automatically generated whenever any outstanding offers are rejected. This provides us with rich variation in the timing of offers, which is crucial for identifying the effect of an early offer.

To explain the early-offer effect, we present a model of university admissions with learning costs and regret. Learning costs include the time and effort necessary for students to discover their valuation of a university program. This assumption is supported by direct survey evidence that we have collected. The survey shows that students search for information about programs in the admission process and do so more often for programs that have already made them an offer. Furthermore, we assume that a student experiences regret, as a disutility, when having accepted the admission offer from a program that turns out to be of a lower quality than a foregone offer (Loomes and Sugden, 1982).

The stylized model assumes that a student optimally learns about the value of her early offer, while another program may extend an offer to her in the later centralized phase. She will accept the early offer if its value is high enough; if its value is sufficiently low, she will rank the early offer below the other program. When the early offer is of intermediate value, she will learn about the other program and will rank the two according to their observed quality. Importantly, the student anticipates possible regret and thus dislikes accepting the late offer without learning its value. Therefore, for low intermediate values of the early offer, the student optimally learns the other program's value and ranks both programs accordingly. By contrast, in the absence of regret, for these values of the early offer, she would rank the potential late offer higher than the early offer without additional learning.

The model thus introduces an asymmetry and generates a higher acceptance probability of the early offer—an endowment effect (Kahneman et al., 1990). While the early-offer effect may also be consistent with an endowment effect due to loss aversion, our model captures the need to acquire information for preference formation.

We also discuss alternative explanations. We first show that it is unlikely that the early-offer effect is driven by students' need to have a head start in the housing market. Specifically, the effects are stronger for students who applied to programs in their hometown, where they usually do not need to find housing. We also exclude that the early-offer effect is driven by a student's spontaneous feeling of relief for having secured herself a seat, because students wait an average of nine days to accept an offer. Moreover, it is possible that students respond positively to early offers because programs reveal that they value the student highly by making such offers. We test this explanation by controlling for how programs rank a student and find no evidence for it. Finally, we show that the students' dislike of being assigned through an algorithm is unlikely to explain our findings.

Our empirical results imply the importance of balancing centralization and decentralization in market design. The continuous arrival of offers in a decentralized market facilitates learning about match qualities sequentially, while a standard centralized design helps solve issues like unraveling. DoSV combines some advantages of centralization and decentralization. However, the results also indicate the undue importance of offer arrival time in determining student decision. Taking these effects into account, we propose a novel, hybrid mechanism that improves upon DoSV by modifying the way in which the decentralized phase operates. While the hybrid mechanism allows students to hold multiple offers that arrive over time, and hence learn about programs sequentially as in DoSV, it makes sure that offers are bundled and arrive on pre-determined dates in order to limit the early-offer effect.

Other Related Literature. The assumption of known-and-fixed preferences has received little attention in the market-design literature. Recently, it has been documented that revealed preferences in matching markets are inconsistent with this assumption. Narita (2016) finds that students reveal contradictory preferences in the main round and the subsequent reapplication round of school choice in New York City. The allocation of seats for medicine in Germany provides students with the possibility to submit rank-order lists that induce a lottery over outcomes; Dwenger et al. (2018) show that many students intentionally choose a lottery instead of a deterministic outcome. Similar to our findings, these results imply a more complex process of preference formation than commonly assumed.

Costly acquisition of information about preferences is a recent topic in the matching literature. For example, Chen and He (2018a,b) investigate theoretically and experimentally students' incentives to acquire information about their own and sometimes others' preferences in school choice. They study the traditional, static DA mechanism where students first acquire information and then submit their rank-order lists.

Sequential learning in our setting is related to the theoretical literature building on Weitzman (1979). A recent study is Immorlica et al. (2018) who investigate information acquisition in a model where students must pay a cost to learn a school's exact value. They study outcomes where students only acquire information on schools that have admitted them, as if the market had resolved and they were "last to market." The paper shows that a mechanism using cutoffs can be used to approximate outcomes with this desirable property. In their model, students have to learn about a school before accepting it. By contrast, students in our setup can accept a school without learning about it. Similar in this respect, Doval (2018) extends the framework of Weitzman (1979) to study optimal sequential learning when a student can accept a school without learning its value. Unlike in our setting, students in her model hold offers from all schools from the outset, and they decide on the order of learning and on the stopping rule.

Our study complements recent work on dynamic matching procedures. A series of papers, some of them inspired by college admission procedures in practice (Gong and Liang, 2017; Bó and Hakimov, 2018), investigate dynamic, or iterative, versions of the DA mechanism (Echenique et al., 2016; Klijn et al., 2019; Bó and Hakimov, forthcoming).[4] The iterative DA differs from DoSV in a number of respects (see Section 4 for details). Most importantly, this literature studies single-offer centralized procedures following the protocol of DA under the assumption that students know their preferences and that these preferences are fixed.

Preference formation has been studied outside the market design literature. For example, a behavioral aspect of preference formation is described by Elster (1983) where agents adjust their preferences according to what is available to them. Experimental evidence for this "sour grapes" effect emerges from recent experiments by Alladi (2018) who finds that the attractiveness of an option increases with its accessibility. Another example is a model of consumer search, Dzyabura and Hauser (forthcoming), in which consumers revise their weights on product attributes in the process of searching for products.

There is a large empirical literature on the determinants of college choice (see, e.g., Manski and Wise, 1983, for an early contribution). This literature investigates the determinants of preferences rather than studying the process of preference formation. Additionally, early admission offers play an important role in college admissions in the U.S. (Avery et al., 2003; Avery and Levin, 2010). Colleges want to admit students who are enthusiastic about attending, and early admission programs give students an opportunity

[4]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. Indeed, there is a growing literature showing that, even under the standard 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, 2019) or in the field (Chen and Pereyra, 2015; Artemov et al., 2017; Shorrer and Sóvágó, 2017; Hassidim et al., 2018; Rees-Jones, 2018).

to signal this 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 shows direct evidence from a survey and discusses alternative hypotheses. We develop a model of university admissions with learning costs and regret that generates predictions consistent with the findings. Implications of our theoretical and empirical results for market design are discussed in Section 4. Finally, Section 5 concludes.

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 get a seat at a university in the program of her choice. However, starting in the 1960s, a steep increase in the number of applicants created an overdemand for seats especially in medicine, and entry barriers were introduced based on the final grade in the *Abitur* (Numerus clausus). 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, a steady decline in the number of programs administered through the ZVS clearinghouse occurred. The main reasons were that universities wanted to gain control of their admission process, and new bachelor and master's programs were created as part of the Bologna reforms that did not fit into the broad categories of programs that the clearinghouse used for its central allocation mechanism. By 2005, the only programs administered by the ZVS were medicine, pharmacy, dental medicine, veterinary medicine, and psychology (the latter only until 2010/11). Seats for these programs are allocated according to a procedure involving quotas that is regulated by law.[5] At the same time, severe congestion problems for many other programs appeared in the market.

[5]For an analysis of the ZVS procedure, see Braun et al. (2010), Westkamp (2013), and Braun et al. (2014).

A re-organization 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 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 and universities participating in this procedure has increased steadily.[6] The largest number of seats is allocated in economics and business administration, and the second largest subject is psychology where the majority of programs participate in the DoSV.

1.2 The DoSV Procedure: Integrating Centralization and Decentralization

The DoSV procedure is based on the university-proposing deferred acceptance mechanism (Gale and Shapley, 1962; Roth, 1982). However, the first phase of the mechanism extends over several weeks and allows for interactions between students and universities that are similar to those in a decentralized market. In particular, while each student submits a rank-order list of programs, she does not have to commit to a ranking before the mechanism starts. She only has to finalize her rank-order list at the end of the first phase, that is, after possibly having received some offers. This phase provides us with a unique data set of offers to students, their re-ranking of programs, offer acceptances and rejections in real time. It allows us to observe the effects of early offers on the final admission outcome.

The admission procedure is divided into several phases, depicted in Figure 1. 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 only possible for a small number of programs.

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

[6] In the procedure for the winter term of 2015/16, 89 universities with 465 programs participated, compared to 17 universities with 22 programs which participated in the first year that 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 the 432,000 students who started university that year. Thus, roughly 18 percent of first-year undergraduate students were assigned to a program through the DoSV in 2015/16.

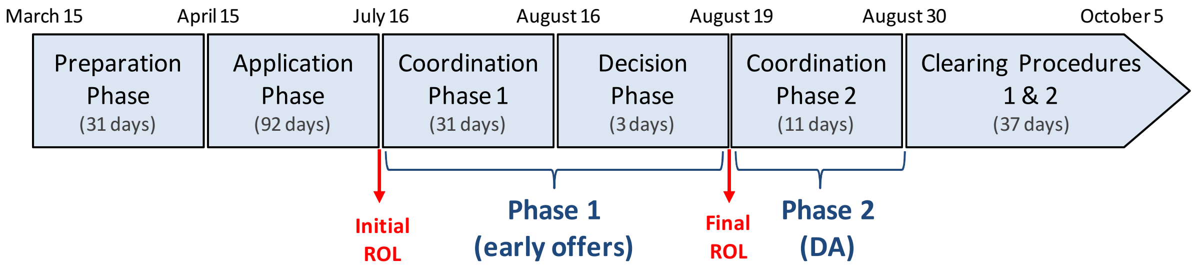


Figure 1: Timeline of the DoSV Procedure (Winter Term)

Notes: This figure displays the different phases of the DoSV procedure. 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 DA mechanism is run.

Application Phase (April 15–July 15): Students apply to at most 12 university programs.[7] They have to submit their application directly to each of the universities. The universities transmit the applications they have received for their programs to the clearinghouse. A student's initial ROL of programs is based on the time her applications arrive at the clearinghouse, although students may actively change the ordering at any time during this phase.

Coordination Phase 1 (July 16–August 15): The universities' admission offices create rank-order lists of applicants for each program following a set of pre-specified criteria (*Abitur* grade, waiting time since high school graduation, etc.) and transmit them to the clearinghouse. The universities cannot manipulate their rankings of applicants although they may have some scope as to when the lists are transmitted.[8] Via automated emails, the clearinghouse sends admission offers to the top students on the list up to the program's capacity. We define these offers as *early offers*. 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 on the list is automatically generated. The students are informed about their rank on each of the rank-order lists from universities, the number of seats available for each list, and the number of students ranked above them who are no longer competing for a seat.

Decision Phase (August 16–18): Starting on August 16, universities can no longer

[7]This is similar to constrained school choice in which students cannot apply to more than a certain number of schools (Haeringer and Klijn, 2009; Calsamiglia et al., 2010).

[8]Details on the process through which universities rank applicants and the role of quotas are provided in Appendix A.1. Strategic aspects of the timing of offers are discussed in Section 4.

submit their rankings of applicants to the clearinghouse or adjust their programs' capacities. However, early offers continue to be generated until August 18 because students may still reject offers received in Coordination Phase 1. Students are informed that they are entering the last days of the decentralized phase of the procedure and are encouraged to finalize their ROL.

Coordination Phase 2 (August 19–29): At the beginning of this phase, a program (a) may have some seats taken by students who have accepted an early offer from this program and left the procedure; (b) may have seats/offers tentatively held by some students who have kept their early offer from this program but chose to stay on; and (c) may have some available seats because some of its early offers have been rejected. Meanwhile, a student (i) may have left the procedure by accepting an early offer; (ii) may have kept an early offer and chosen to stay on with the final ROL of programs; (iii) may not have received any offer and stayed on with the final ROL of programs; or (iv) may have exited the procedure, thereby rejecting all offers. Taking the remaining students and available or tentatively held seats, the clearinghouse runs a program-proposing deferred-acceptance algorithm as follows:

(A) Following the ranking over students provided in Coordination Phase 1, a program sends admission offers to students ranked at the top of its list 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.

(B) Students with multiple offers keep the one from the most preferred program according to their final ROLs and reject all other offers. All other students are inactive.

(C) Steps (A) and (B) are repeated until every program either has no seats left or has vacant seats but no more students to make offers to. Then, each student is assigned to the program she holds, if any.

Coordination Phase 2 uses the program-proposing DA where students start out with their highest-ranked offer from Coordination Phase 1 and the Decision Phase. They can never do worse than this offer, while they may receive an offer from a program that is ranked even higher in their final ROL. Coordination Phase 2 is automated and guarantees that the final admission outcome of the DoSV procedure is stable, under the assumption that students who left the clearinghouse before Coordination Phase 2 have accepted their most preferred program among all they have applied to and could have received an offer from. This means that there is no program and student who prefer to be matched to each other rather than to the match partner prescribed by the mechanism.

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

For the analysis of students' choices, we will mainly 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 it Phase 1. Furthermore, Coordination Phase 2 is also of interest for our investigation, and we denote it by Phase 2. Recall that offers that students receive in Phase 1 are defined as *early offers*. We define the rank-order list over programs that the clearinghouse has recorded for each student at the beginning of Phase 1 the *initial ROL* while the rank-order list at the end of Phase 1 is defined as the *final ROL*. A program is defined as *feasible* for 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.[9] 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.

1.3 Data

The comprehensive micro-data set that we use covers the application and admission procedure in 2015 for the winter term of 2015/16. It includes 183,088 students who applied to 465 programs at 89 universities. Basic socio-demographic information about the students is available (gender, age, postcode), and we know the *Abitur* grade for 83 percent of students.[10] Furthermore, we observe the students' ROLs at any point in time, the programs' rankings of applicants, the offers made by the programs throughout the process, the acceptance and rejection of offers by students, and the final admission

[9]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 et al., 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.

[10]In the data, the *Abitur* grade is missing for about half of the students, but we can infer it in most cases based on how students are ranked under the programs' *Abitur* Quota. See Appendix A.1 for details about the DoSV data, the imputation of missing *Abitur* grades, and the sample restrictions.

outcome.

We exclude students with missing socio-demographic information as well as students who apply to specific programs with complex ranking rules. These are mostly students who want to become teachers and who 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 programs. This leaves us with 64,876 students.

In Table 1, we provide summary statistics of students, their ROLs, the number of feasible programs that they ranked, the offers received, and the admission outcome. On average, applicants to standard programs applied to 2.9 programs (column 1). The corresponding figure is 4.2 among the students who applied to more than one program (column 2), and 4.7 among those who applied to at least two feasible programs and accepted an offer (column 3). Panel C reveals that 58.1 percent of students who applied to at least two programs (column 2) had at least one feasible program, that is, they would have received at least one offer in the course of the procedure if they did not leave the procedure before Phase 2. Importantly for our analysis, more than half the students who applied to more than one program received one or more offers in Phase 1, and around a quarter (24.7 percent) accepted an offer in Phase 1 (Panel D). Among them, almost 40 percent accepted an offer that was not their first choice according to their initial ROL. Table 1 also indicates that only half of the students ended up accepting an offer from a program in either Phase 1 or Phase 2.[11] Note that this does not mean that these students did not find a seat at a university, since they could 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 admission 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 ("finalized their ROL"), when they receive their first offers from university programs ("received an offer") and when they exit the procedure. An important takeaway for our study is that the first offers sent out by the programs are spread out over Phase 1 (see also Figure C1 in the Appendix). It is

[11] Throughout the analysis, we use the expression "accept an offer" to designate either students who actively accepted an early offer in Phase 1 or students who were assigned by the computerized algorithm in Phase 2.

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)
Panel A. Students			
Female	0.579	0.496	0.558
Age	20.8	20.5	20.7
	(3.2)	(2.6)	(3.1)
Abitur percentile rank (between 0 and 1)	0.50	0.51	0.65
	(0.29)	(0.29)	(0.28)
Panel B. Applications			
Length of initial ROL (on July 15)	2.9	4.2	4.7
	(2.6)	(2.7)	(2.9)
Actively ranked programs before Phase 1[a]	0.547	0.226	0.320
Re-ranked 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*)	0.622	0.610	0.583
	(0.446)	(0.420)	(0.417)
Average distance to ranked programs (km)[c]	111	120	126
	(127)	(119)	(122)
Top-ranked program (on July 15): field of study[d]			
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
Panel 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
Panel 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
of which: not initially top-ranked	0.262	0.399	0.369
Participated in Phase 2	0.722	0.708	0.444
Accepted an offer in Phase 1 or Phase 2	0.448	0.518	1.000
Number of days between offer arrival and acceptance[e]	9.19	9.62	9.11
	(8.73)	(8.75)	(8.30)
Number of students	110,781	64,876	21,711

Notes: The 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 non-missing values and who applied to standard programs only, i.e., after excluding students who applied to specific "multiple course" programs (*Mehrfachstudiengang*), which consist of two or more sub-programs with complex assignment rules. Column 2 further restricts the sample to students who initially applied to two programs or more. Column 3 considers only students who applied to at least two feasible programs and who either actively accepted an early offer during Phase 1 or were assigned to a program through the computerized algorithm in Phase 2. [a] A student is considered as having actively ranked programs before Phase 1 if she only applied to one program or if she manually altered the ordering of her applications before July 15, which by default is from the oldest to the most recent program included in her ROL. [b] A student is considered as having re-ranked her choices during Phase 1 if either the final ROL is different from the initial ROL or if the student accepted an early offer from a program that she did not initially rank in first position. [c] The distance between a student's home and a program is computed as the cartesian distance between the centroid of the student's postcode and the geographic coordinates of the university in which the program is located. [d] For programs combining multiple fields of study, each field is assigned a weight equal to $1/k$, where k is the number of fields. [e] 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 automatically assigned to their best offer in Phase 2, the acceptance date is set to the first day of Phase 2, i.e., August 19, 2015.

exactly this arrival of offers at different points in time that allows us to identify the effect of early offers on admission outcomes. We will show below that the offer arrival time is not correlated with the initial preferences of the students and that early offers are not, on average, made by more selective programs. Instead, the time at which programs submit their rankings to the clearinghouse is determined by administrative processes within the universities.[12]

Almost all student exits from the DoSV take place in phases 1 and 2. During Phase 1, students leave when they have either accepted an offer or canceled all applications. The number of exits has a spike at the beginning of Phase 2 when the clearinghouse automatically accepts an 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 the students do not get an offer and therefore stay in the procedure until the very end.

Next, we disaggregate the exits by their reason for leaving the procedure. Figure 3 shows that 22.2 percent of students actively accept an offer during Phase 1, 22.3 percent receive their best offer during Phase 2 when the DA is run (of which two thirds are automatically removed on the first day because they had received an offer from their top-ranked program), 14.3 percent cancel their applications at some point while the remaining 40.9 percent participate in Phase 2 but receive no offer.

2 Early Offers and Acceptance Probability: Empirical Results

We now turn to our main question of whether the order in which a student receives offers affects the admission outcome. We provide empirical results to test the following hypotheses: (i) conditional on a program being feasible, having received an early offer from the program increases the probability of accepting the offer from that program; and (ii) the earlier the offer arrives, the larger the effect on the offer-acceptance probability.

[12]According to information from the *Stiftung für Hochschulzulassung*, the point in time when the rankings are transmitted to the clearinghouse depends on the number of personnel available in the admission 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 the general policy of a university as to whether to check all applications for completeness or instead to accept applicants conditionally.

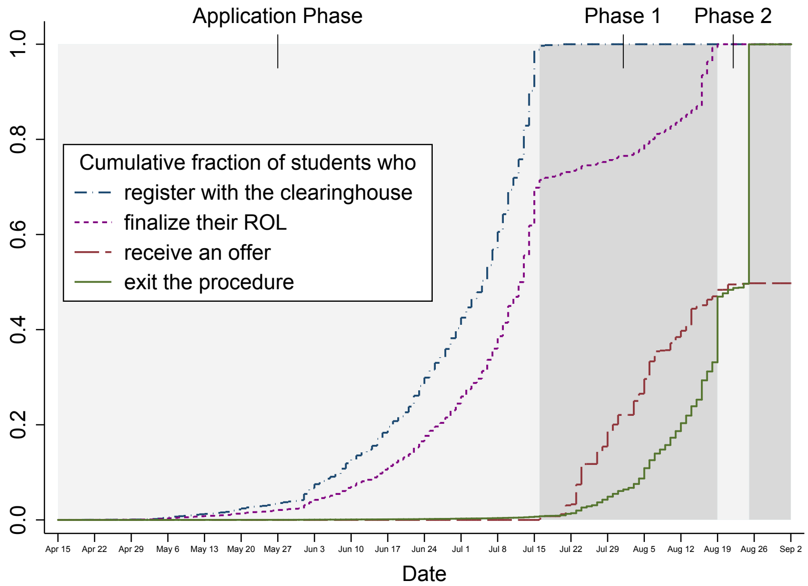


Figure 2: Activities during the DoSV Procedure (Winter Term of 2015/16)

Notes: This figure displays the evolution of several key indicators throughout the DoSV procedure, based on data from the *Dialogorientierten Serviceverfahren* (DoSV) for the winter term of 2015/16: (i) cumulative fraction of students who register with the clearinghouse during the application phase as well as during later phases (dash-dot line); (ii) cumulative fraction of students who finalize their rank-order list 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 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 (solid line).

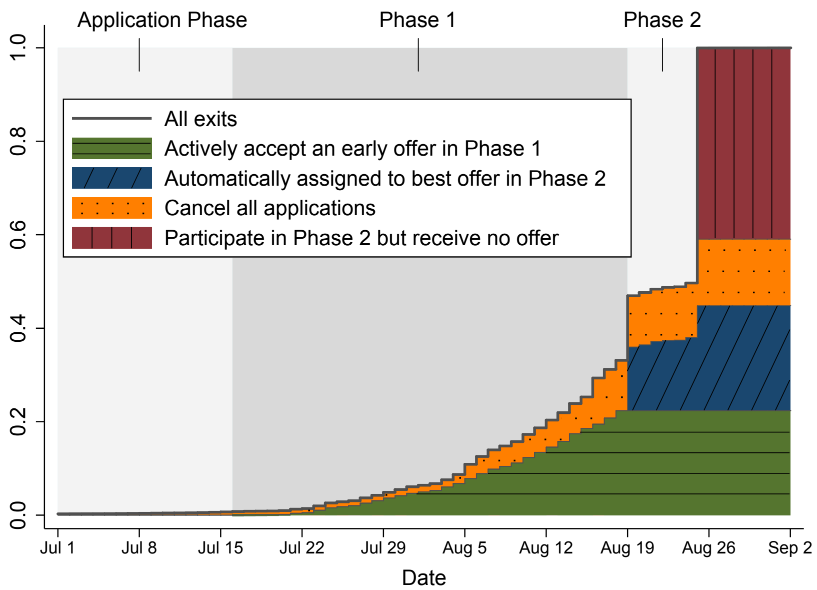


Figure 3: Reasons for exiting the DoSV Procedure (Winter Term of 2015/16)

Notes: This figure shows the cumulative admission outcomes of students throughout the DoSV procedure, based on data 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 accept their best offer during Phase 2 (area with diagonal hatching); (iii) cumulative fraction of students who cancel their application (dotted area); and (iv) cumulative fraction of students who participate in Phase 2 but receive no offer (area with vertical hatching).

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 an offer from the program, provided that she remains in the procedure until in Phase 2 while holding other students' behaviors constant. Therefore, infeasible programs are irrelevant to a student's offer acceptance decision. Conceptually, if offers arrive exogenously for the feasible programs, common matching models predict no early-offer effect on acceptances, because of the known-and-fixed-preferences assumption.

2.1 Empirical Approach

To empirically assess whether students are more likely to accept early offers, we develop a conditional logit model. Let F_i be student i's set of feasible programs, which are indexed by k. For all i and all k in F_i:

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

where $U_{i,k}$ is the utility to student i of feasible program k (at the time of making the ranking or acceptance decision), $\boldsymbol{Z}_{i,k}$ is a row vector of student-program-specific characteristics, and $\epsilon_{i,k}$ is i.i.d. type I extreme value (Gumbel) distributed.

Utility-maximizing students accept the offer from their most-preferred feasible program. Therefore, we can write i' choice probability for $k \in F_i$ as follows:

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

The assumption of utility maximization is not restrictive, since our analysis is conditional on the set of applications that a student has already submitted.[13] Focusing on the feasible programs is innocuous even if the student has not received offers from some of the programs, because there is no cost imposed by the DoSV procedure for the student to top-rank a program and accept its offer in Phase 2.

To investigate whether receiving a potential early offer from program k in Phase 1 (as

[13] Endogenizing the application decision, Fack et al. (2019) show that being matched with the most-preferred feasible program is also a plausible equilibrium outcome in a game with incomplete information. However, as in the traditional literature, they assume that student preferences are private information and are held constant in the admission process.

opposed to receiving it in Phase 2) increases the probability of i accepting k's offer, the random utility model is specified as follows:

$$U_{i,k} = \theta_k + \delta\, \mathit{EarlyOffer}_{i,k} + \gamma d_{i,k} + \boldsymbol{X}_{i,k}\lambda + \epsilon_{i,k} \tag{2}$$

where θ_k is the fixed effect of program k, $d_{i,k}$ is the distance between student i's postcode and the address of the university where the program is located, $\mathit{EarlyOffer}_{i,k}$ is a dummy variable that equals one if i receives an offer from program k during Phase 1 (i.e., up to August 18), and $\boldsymbol{X}_{i,k}$ are other student-program-specific controls. Importantly, as we restrict our analysis to feasible programs, $\mathit{EarlyOffer}_{i,k}$ is defined as zero for programs that made an offer to i in Phase 2 or could have made an offer in Phase 2 if the student had not exited. $\boldsymbol{X}_{i,k}$ controls for whether the program is in the student's region (*Land*) and how the student is ranked by the program among all its applicants (in percentile between 0 – lowest ranked – and 1 – highest ranked).[14] The coefficient of interest, δ, is thus identified by the within-student variation in the timing of offer arrival, conditional on programs' observed heterogeneity and unobserved average quality.

2.2 Identifying Assumption: Exogenous Arrival of Offers

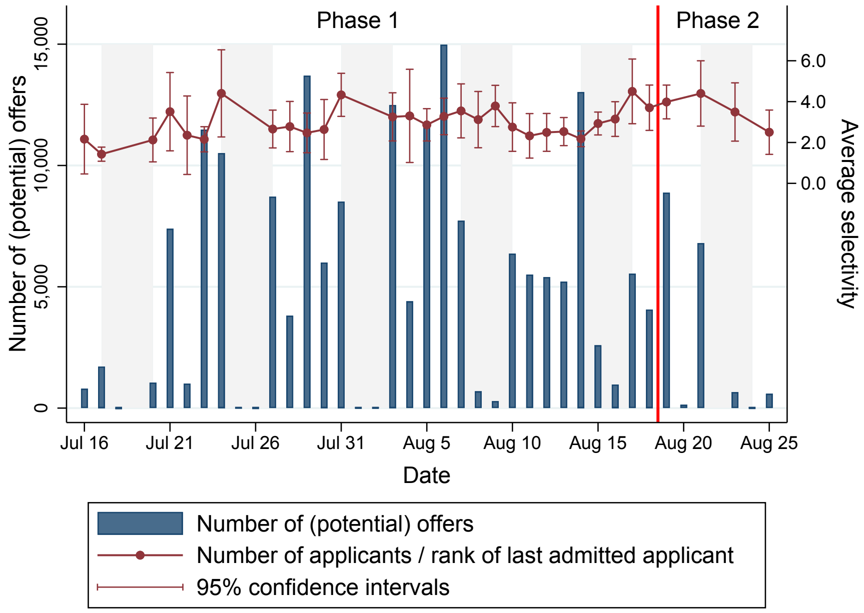
One potential concern is that the early offers might be more attractive than those arriving later for reasons unrelated to their arrival time. The specification in Equation (2) requires that $\mathit{EarlyOffer}_{i,k}$ is independent of utility shocks ($\boldsymbol{\epsilon}$) conditional on other controls. To test this identifying assumption, we study the program selectivity of the offers that are made over time. After calculating the selectivity measure for every program, we take the average selectivity of 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 ratio of the number of a program's applicants to the lowest rank among the students who have received an offer from the program. A higher ratio indicates a higher degree of selectivity. In Panel (b), the measure is the average *Abitur* percentile (between 0 and 1) of students applying to the program. The higher the average *Abitur* percentile, the higher the degree of selectivity.

In either of the two panels, there is no clear pattern over time, which is consistent

[14] We compute how a student is ranked by a given program using the program's ranking of all its applicants under the *Abitur* quota.

(a) Ratio of the Number of a Program Applicants to the Lowest Rank of its Admitted Students



(b) Average *Abitur* Percentile of a Program's Applicants

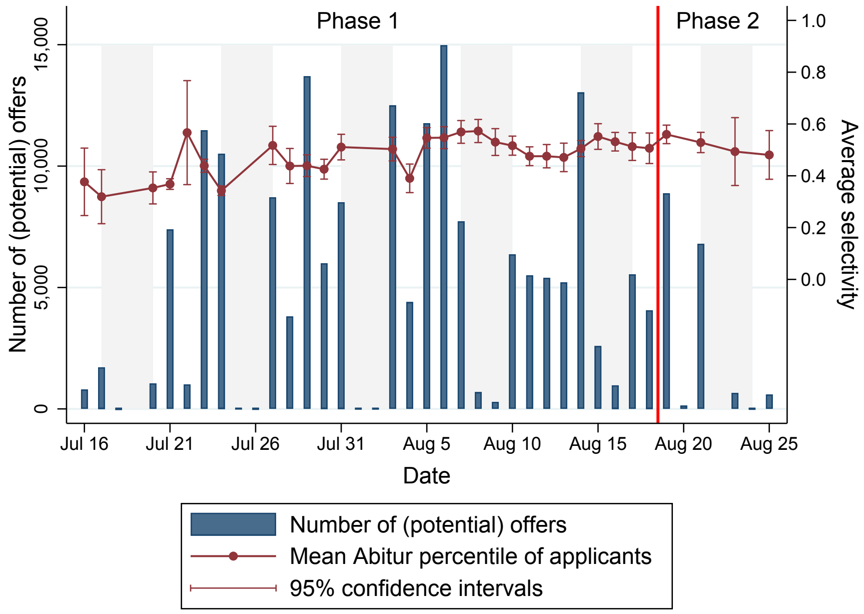


Figure 4: Offer Arrival Time and Program Selectivity

Notes: The 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 of programs sending out offers on a given day, with 95 percent confidence intervals denoted by vertical T bars. In Panel (a), the selectivity of each program is proxied by the ratio between the number of the program's applicants and the rank of the last student receiving an offer from the program, with weights equal to the number of potential offers made by each program on that day. In Panel (b), the selectivity of each program is proxied by the average *Abitur* percentile (between 0 and 1) of the program's applicants. The selectivity of potential offers made on a given day is computed as the weighted average of the program selectivity measure. The selectivity measures are not shown for days in which less than 150 potential offers were made, which mostly coincide with weekends (denoted by gray shaded areas).

with the timing of offers being mostly determined by the administrative processes within the universities rather than by strategic considerations. If anything, the very early offers tend to come from slightly less selective programs.

We further test the time trends in offers based on regression analyses. Column 1 of Table 2 shows how the first selectivity measure on each day is correlated with the number of days that have elapsed since the start of Phase 1. The coefficient is not statistically significant. Column 3 repeats the same regression but with the second selectivity measure as the dependent variable. The coefficient turns out to be positive and significant, implying that earlier offers are from marginally less selective programs. Columns 2 and 4 regress the selectivity measures on week dummies. Indeed, the results show that the very early offers are less attractive.

Additionally, in Table 5 (columns 1–3) we show that early offers are not correlated with how students rank the offer-issuing 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 that only includes students who applied to at least two feasible programs and who either actively accepted an early offer in Phase 1 or were automatically assigned to their best offer 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 as control variables. The program fixed effects capture observed and unobserved program-specific characteristics, such as selectivity or faculty quality, that 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 very first offer (*FirstEarlyOffer*).[15] Students are even more likely to accept the very first offer,

[15] In our sample, the average time between the first and second early offers is 4.89 days among the

Table 2: Offer Arrival Time and Program Selectivity—Regression Analysis

	Dependent variable: selectivity of program making offer			
	Selectivity measure 1: Ratio of number of applicants to rank of last admitted student		Selectivity measure 2: Average *Abitur* percentile of applicants	
	(1)	(2)	(3)	(4)
Number of days elapsed since start of Phase 1	0.0168		0.0045***	
	(0.0199)		(0.0010)	
Week of (potential) offer arrival				
Week 1 (July 16–22)		−0.379		−0.117***
		(0.515)		(0.028)
Week 2 (July 23–29)		−0.404		−0.062
		(0.474)		(0.033)
Week 3 (July 30–August 5)		ref.		ref.
Week 4 (August 6–12)		−0.263		0.034
		(0.317)		(0.026)
Week 5 (August 13–19)		−0.112		0.023
		(0.498)		(0.024)
Week 6 (August 20–25)		0.853*		0.026
		(0.368)		(0.022)
Number of potential offers	192,840	192,840	192,840	192,840

Notes: This table reports regressions for testing whether the timing of offers is correlated with the selectivity of the programs sending out these offers. Program selectivity is proxied by two measures: (i) the ratio between the number of the program's applicants and the rank of the last student receiving an offer from the program; and (ii) the average *Abitur* percentile (between 0 and 1) of the program's applicants. The unit of observation is a potential offer, i.e., an offer that was either sent out to a student or that could have been sent out had the student not canceled her application to the program. The day of arrival of each (potential) offer is identified as the day it became feasible to the student. In all regressions, the dependent variable is the selectivity of the program sending out the offer on a given day. In columns 1 and 3, the program selectivity 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) being set as the omitted category. Standard errors clustered at the day level are shown in parentheses. *: $p < 0.1$; **: $p < 0.05$: ***: $p < 0.01$.

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 (column 3), how the program ranks the student (column 4), and the chances of a student not receiving an offer from the program in 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. This allows for the possibility that a student accepts an early offer because she does not expect to receive other offers in Phase 2.

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 length between the first and second (potential) early offers is 5.38 days.

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 (in thousand km)			−9.36***	−9.37***	−9.37***
			(0.33)	(0.33)	(0.33)
Distance to university (in thousand km) – 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 0 and 1)				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
Number of feasible programs	66,263	66,263	66,263	66,263	66,263
B. Marginal effects on utility (measured in distance)[a]					
(Average distance to ranked programs: 126 km)					
EarlyOffer (in km)			−59	−58	−61
FirstEarlyOffer (in km)			−78	−77	−79
C. Marginal effects on acceptance probability of feasible programs[b]					
(Baseline acceptance probability: 38.5%)					
EarlyOffer (percentage points)	10.4	8.7	8.4	8.3	8.7
	(1.5)	(1.4)	(1.6)	(1.5)	(1.6)
EarlyOffer (%)	31.9	26.7	27.0	26.5	27.9
	(8.6)	(6.9)	(6.9)	(6.8)	(7.2)
FirstEarlyOffer (percentage points)		11.6	11.5	11.3	11.8
		(1.7)	(2.0)	(2.0)	(2.1)
FirstEarlyOffer (%)		35.9	37.4	36.8	38.3
		(10.0)	(10.3)	(10.1)	(10.7)

Notes: This table reports the estimates from a conditional logit model for the probability of accepting a program among feasible programs. The sample only includes students who applied to at least two feasible programs and who either actively accepted an early offer during Phase 1 or were automatically assigned to their best offer in Phase 2. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., to the programs from which she could have received an offer by the end of Phase 2. *EarlyOffer* is a dummy variable, equal to one if the program became feasible to the student during Phase 1 and zero if it became feasible in Phase 2. *FirstEarlyOffer* is a dummy variable, equal to one if the program is the first to have become feasible to the student during Phase 1. A program's ranking of students is measured using the ranking under the *Abitur* quota. The chances of not receiving an offer from a program in Phase 2 are proxied as follows: a value of zero is assigned to students who received an early offer from the program in Phase 1; for students who did not receive an offer from the program in Phase 1, we use the ratio between the student's rank under the most favorable quota and the rank of the last student under this quota who received an offer from the program in Phase 1. *: $p < 0.1$; **: $p < 0.05$: ***: $p < 0.01$.

[a] The marginal effect of a non-first 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 very first offer.

[b] For the marginal effect 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 (i) set *EarlyOffer* to one and *FirstEarlyOffer* to zero, and (ii) set *EarlyOffer* to zero and *FirstEarlyOffer* to zero. The baseline probability is the average of the second prediction across students; and 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.

All these results show a positive early-offer effect on offer acceptance. To quantify the effects, we use distance as a "numeraire." At the sample mean of distance (126 km, as shown in column 3 of Table 1), an early offer that is not the very first offer gives the program a boost in utility equivalent to reducing the distance by 61 km, based on the results in column 5.[16] The very first offer has an even larger effect, amounting to a reduction of 79 km.

Another way to evaluate the magnitude of the early-offer effect is to calculate its impact on the probability of offer acceptance (Panel C of Table 3). On average, a feasible program is accepted by a student with a probability of 0.385. An early offer that is not the very first one increases the acceptance probability by 8.7 percentage points, or a 27.9 percent increase, based on the estimates in column 5.[17] The effect 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 a 38.3 percent increase, based on the estimates in column 5.

Heterogeneous Effects. We now investigate whether the early-offer effect varies across students, and the results are summarized in Table 4.

We study the potential heterogeneity along a set of student characteristics in columns 2–5: gender, the *Abitur* grade, and the number of feasible programs. Based on the regression with the most comprehensive set of controls, as in column 5 of Table 3, we further add interactions between *EarlyOffer* and a student characteristic as well as between *FirstEarlyOffer* and the student characteristic.

Column 2 of Table 4 shows that female students respond less to early offers, although there is no additional heterogeneity in the effect of the very first early offer. Students with a better *Abitur* grade respond less to the very first offer, but do not behave differently for other early offers (column 3). The number of feasible programs among those ranked by a student does not change the early-offer and first-early-offer effects (column 4).

[16]To calculate the marginal effect of this non-first 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 very first offer.

[17]For this marginal effect, we measure the difference between the following two predictions on offer acceptance behavior: While keeping all other variables at their original values, we (i) set *EarlyOffer* to one and *FirstEarlyOffer* to zero, and (ii) set *EarlyOffer* to zero and *FirstEarlyOffer* to zero. The baseline probability is the average of the second prediction across students; and 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.

Table 4: 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 0 and 1)			−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 0 and 1)			−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	Yes	Yes	Yes	Yes	Yes
Program's ranking of student	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
Number of feasible programs	66,263	66,263	66,263	66,263	66,263

Notes: This table reports the estimates from a conditional logit model for the probability of accepting a program among feasible programs. The sample only includes students who applied to at least two feasible programs and who either actively accepted an early offer during Phase 1 or were automatically assigned to their best offer in Phase 2. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., to the programs from which she could have received an offer by the end of Phase 2. *EarlyOffer* is a dummy variable, equal to one if the program became feasible to the student during Phase 1 and zero if it became feasible in Phase 2. *FirstEarlyOffer* is a dummy variable, equal to one if the program is the first to have become feasible to the student during Phase 1. *: $p < 0.1$; **: $p < 0.05$: ***: $p < 0.01$.

Early-Offer Effect on Students' Re-Ranking Behavior. To provide additional evidence, we extend the above analyses to students' re-ranking behavior, which is possible due to the unique data set that documents students' ROLs at any point in time. Specifically, we use the initial and final ROLs of each student to investigate whether the ranking of programs is influenced by early offers.

As above, we restrict our attention to feasible programs. A final ROL is constructed as follows. (i) For a student who actively accepted an early offer during Phase 1, we only code 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 as her final ROL the partial order of feasible programs in the ROL that she submitted in Phase 2, up to the first program that made her an early offer in Phase 1. Programs ranked below this highest ranked early offer are only coded to be less preferred than those ranked above. Their relative rank order is ignored because it is payoff-irrelevant for the student.

By using rank-order logit (or exploded logit), we obtain the results in Panel A of Table 5. 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 positive correlation between the initial rank order of a program and receiving an early offer from that program, which is consistent with the hypothesis that early offers are not from more attractive programs.

Columns 4–6 of Panel A reveal that receiving an early offer induces a student to rank that program higher in her final ROL. Similarly, the very first 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 the acceptance probability that are in Table 3. In Panel B of Table 5, at the sample mean of distance (126 km), the very first 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 59 km on average.

Panel C of Table 5 presents the marginal early-offer effects on the probability of top-ranking the program in one's ROL. An early offer that is not the very first offer increases the top-ranking probability by 8–10 percentage points, or a 25–30 percent increase (columns 4–6).[18] The first early offer has a larger marginal effect. It increases the acceptance probability by 11 percentage points, or a 33–36 percent increase (columns 5–6).

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

Since there is some evidence that the very early offers are from slightly less selective programs, we consider the possibly heterogeneous effect of early offers during the first two weeks of Phase 1. Table C2 in the Appendix 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 in the regressions. Table C3 in the Appendix reveals that these further controls do not change our results.

[18] The calculations are similar to those on offer acceptance probability. See the details in footnote 17.

Table 5: Initial vs. Final Ranking of Feasible Programs—Rank-Order Logit Model

	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 (in thousand km)			−5.44***			−9.15***
			(0.21)			(0.32)
Distance to university (in thousand km) – 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 0 and 1)			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
Number of feasible programs	66,263	66,263	66,263	66,263	66,263	66,263
B. Marginal effects on utility (measured in distance)[a]						
(Average distance to ranked programs: 126 km)						
EarlyOffer (in km)						−59
FirstEarlyOffer (in km)						−76
C. Marginal effects on probability of ranking feasible program as top choice[b]						
(Baseline acceptance probability: 38.5%)						
EarlyOffer (percentage points)				9.7	8.3	8.3
				(1.5)	(1.3)	(1.5)
EarlyOffer (%)				29.7	25.2	26.6
				(7.9)	(6.4)	(6.8)
FirstEarlyOffer (percentage points)					10.8	11.1
					(1.6)	(1.9)
FirstEarlyOffer (%)					33.3	35.8
					(9.1)	(9.8)

Notes: This table reports estimates from a rank-order logit model for the probability of observing a student's initial and final rank-order lists (ROL) of feasible programs. The sample only includes students who applied to at least two feasible programs and who actively accepted an early offer during Phase 1 or were automatically assigned to their best offer in Phase 2. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., to the programs from which she could have received an offer by the end of Phase 2. Columns 1 to 3 consider students' initial ROLs while columns 4 to 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. The final ROL is constructed as follows: (i) when a student actively accepted an early offer during Phase 1, we only assume that she prefers the accepted offer to all other feasible programs in her ROL; (ii) when a student was assigned to a program in Phase 2, we use as her final ROL the partial order of feasible programs in the ROL that she submitted in Phase 2, up to the first program that made her an early offer in Phase 1—programs ranked below this highest ranked early offer are only assumed to be less preferred than those ranked above (their relative rank order is ignored). *EarlyOffer* is a dummy variable, equal to one if the program became feasible to the student during Phase 1 and zero if it became feasible in Phase 2. *FirstEarlyOffer* is a dummy variable, equal to one if the program is the first to have become feasible to the student during Phase 1. *: $p < 0.1$; **: $p < 0.05$: ***: $p < 0.01$.

[a] The marginal effect of a non-first 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 very first offer.

[b] For the marginal effect on top-ranking probability, we measure the difference between the following two predictions on top-ranking behavior: While keeping all other variables at their original values, we (i) set *EarlyOffer* to one and *FirstEarlyOffer* to zero, and (ii) set *EarlyOffer* to zero and *FirstEarlyOffer* to zero. The baseline probability is the average of the second prediction across students; and 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 the analysis of student ranking behavior, one may be concerned that some students' initial ROLs may not be meaningful because students know that they can change them until the end of Phase 1. In Table C4 in the Appendix, we restrict the sample to students who submitted an initial ROL that they had actively chosen. 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 from the full sample.

3 What Drives the Early-Offer Effect?

In this section, we investigate possible reasons for the finding that students are influenced by the time at which offers arrive. We present the results from a survey that we conducted among students. We then discuss a number of potential explanations for our findings. Finally, we introduce a model with costly learning and regret that can account for the results from the data and the survey.

3.1 Evidence from a Survey

In order to shed light on the students' decision-making process and to better understand what motivates their observed behaviors, 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, the year for which we obtained the administrative data. Information about the setup of the survey and the complete list of questions are provided in Appendix A.2.

Table 6 is structured along four different groups of survey respondents in Panels A to D. Panel A considers all respondents and indicates that two thirds applied to more than one program. Among this subgroup (described in Panel B), a third of the respondents disagree with the statement that, at the time of the application, they had a clear preference ranking of the programs. About one third of the respondents report that they did not have a clear ranking because they needed more research to clarify their preferences, and 24.9 percent agree with the statement that coming up with a preference ranking was very difficult and that they wanted to delay the decision as long as possible. These responses show that a considerable fraction of students are still in the process of making up their mind about programs when they submit their applications.

Table 6: Survey Evidence

	N (1)	Response rate (%) (2)	Agree/Yes (%) (3)
A. All survey respondents			
Applied to more than one program	8,995	83.8	66.2
B. Applied to more than one program			
At the time of application, I had a clear ranking with respect to my preferences[a]	4,944	94.9	66.3
At the time of application, I did not have a clear ranking since I still needed to collect information in order to rank my applications according to my preferences[a]	4,944	91.6	29.6
Getting to a ranking was very difficult, and I wanted to postpone this decision for as long as possible[a]	4,944	91.2	24.9
Received at least one offer	4,944	95.6	83.7
C. Applied to more than one program and received at least one offer			
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]	3,999	81.3	61.4
(b) On average, I spend the same amount of time collecting information on the universities that have made me an offer[a]	3,999	81.3	28.7
(c) On average, I spend less time collecting information on the universities that have made me an offer[a]	3,999	81.3	9.9
Did your ranking change between the beginning of the procedure on July 15 and now?	3,999	88.8	30.2
D. Applied to more than one program, received at least one offer, and re-ranked programs			
I have received some early offers that have changed my perception of the universities[a]	1,072	95.1	29.7

Notes: This table is based on the data from an online survey that was conducted between July 27 and October 10, 2015, among students who participated in the DoSV application and admission procedure for the winter term of 2015/16. The different panels correspond to different subgroups of respondents. Column 1 indicates the number of survey participants in each subgroup. Column 2 reports the response rate (i.e., the fraction of survey participants who did not choose the option "I do not want to answer this question."). Column 3 reports either the fraction of participants who responded Yes (if the question used a dichotomous Yes/No scale), or the fraction who responded that they agree or strongly agree with the statement (if the question used a 5-point Likert scale).
[a] Survey questions originally based on a 5-point Likert scale.

Among respondents who applied to more than one program, 83.7 percent had received at least one offer at the time of the survey.[19] We asked these students how much time they spent learning about programs, depending on whether they had received an offer from the program or not. Panel C indicates that 61.4 percent say they spent more time learning about universities that had made them an offer than about those that had not, as compared to 28.7 percent who said they spent the same amount of time and 9.9 percent who spent less time—the difference between spending more vs. less time being statistically significant at the 1 percent level using a Chi-square test.

[19] Some of these offers may have been made by programs that did not participate in the DoSV.

Finally, the survey results indicate that, among respondents who applied to more than one program and who received at least one offer, 30.2 percent modified their ROL at some point between July 15 (end of the Application Phase) and the time they completed the survey. Among these students (Panel D), 29.7 percent agree with the statement that their perception of the universities was influenced by the early offers they received.

We take these responses as evidence that, at the start of the procedure, many students have incomplete preferences over the set of programs to which they have applied. Furthermore, the answers indicate that students tend to invest more time learning about universities from which they have received an offer than about others, and that early offers influence their perceptions of the programs that made these offers.

3.2 Possible Explanations of the Early-Offer Effect

Early offers are favored by students relative to later offers, and students indicate in the survey that collecting information about universities and forming preferences is costly. We show that these two observations can be reconciled with the help of a model presented in Section 3.3. The idea is that programs with early offers are attractive if students have collected information on them and if students fear regretting the decision to rank another program (of unknown value) higher that may extend an offer later on.

Before turning to the model, we argue that four competing explanations are less plausible than the one we put forward, namely emotional reactions, signaling, gaining a head start in the housing market, and disliking the computerized assignment.

We first consider the possibility that the early-offer effect is driven by a spontaneous reaction, for example a feeling of relief. We fail to find supporting evidence. Specifically, students do not immediately accept an offer upon its arrival (Figure C2 and Table C5 in Appendix C), and the distributions of offers and acceptances on each day of the week differ markedly (Figure C3 in Appendix C). Although almost no offers are made on the weekend, a significant fraction of acceptances occur at this time of the week. Most acceptances are on Mondays and Tuesdays while the number of offers tends to increase as the week moves forward, reaching a peak on Fridays. The mean waiting time before accepting an offer is nine days. Moreover, if the early-offer effect was due to a spontaneous reaction, we would expect the effect to disappear for early offers that are not the very first. Yet, Tables 3 and 5 show that such early offers that do not come in first are still more likely to be accepted.

It is also possible that students respond positively to early offers because they prefer programs that reveal their appreciation by making an early offer.[20] This would imply that students care about how a program ranks them. If the early-offer effect is completely due to a student's appreciation of being ranked highly by an early-offer program, we would expect the effect to disappear after controlling for how a student is ranked by a program (which is observable to her in the DoSV). The results from column 4 in Table 3 where we control for how programs rank a student, show that the early-offer and first-early-offer effects are robust to this control.

It seems plausible that students accept an offer early to have a head start when searching for housing.[21] Whether a student has to find an apartment depends on the location of the program. If a student attends a university in her own municipality, she usually stays with her parents; by contrast, if a student moves to a university in a different region, she typically has to find housing. We can therefore test this housing-demand hypothesis by investigating how the early-offer effect varies by program location.

The results are summarized in Table 7. We estimate the logit model in Equation (1) with the acceptance of a feasible program's offer as the dependent variable. Furthermore, the heterogeneity in the early-offer effect is captured by the interaction between the early offer and program location. The results show that the early-offer effect is largest when the offer is from a program in the student's municipality, while the effect is of the same magnitude for programs in other regions or in the same region but outside the student's municipality. The same pattern holds true for the very first early offer. This is the opposite of what the housing explanation would predict. We thus conclude that housing concerns are unlikely to explain the early-offer effect.

Lastly, it is possible that students dislike being assigned by an algorithm and therefore prefer to accept an offer in Phase 1. An early acceptance would allow them to avoid participating in the computerized procedure of Phase 2. One indication that this is unlikely to drive our findings is that we observe a stronger effect of the *first* early offer than of other early offers. Moreover, almost half the students who are assigned through the algorithm in Phase 2 could have exited before since they ranked an offer as top choice

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

[21]Student dormitories are scarce in Germany, and provide accommodation only for a small subset of students.

Table 7: Early Offer and Acceptance among Feasible Programs—Heterogeneity by Program Location

	(1)
EarlyOffer: Potential offer from program in Phase 1	
× in student's municipality	0.701***
	(0.134)
× in student's region (*Land*) but not in same municipality	0.367***
	(0.117)
× in other region (*Land*)	0.346***
	(0.120)
FirstEarlyOffer: First offer in Phase 1	
× in student's municipality	0.175***
	(0.049)
× in student's region (*Land*) but not in same municipality	0.149***
	(0.034)
× in other region (*Land*)	0.126***
	(0.033)
Controls	
Distance to university (quadratic)	Yes
Program in student's municipality	Yes
Program in student's region	Yes
Program's ranking of student	Yes
Chances of not receiving an offer from program in Phase 2	Yes
Program fixed effects (376 programs)	Yes
Number of students	21,711
Number of feasible programs	66,263

Notes: This table reports the estimates from a conditional logit model for the probability of accepting a program among feasible programs. The sample only includes students who applied to at least two feasible programs and who either actively accepted an early offer during Phase 1 or were automatically assigned to their best offer in Phase 2. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., to the programs from which she could have received an offer by the end of Phase 2. *EarlyOffer* is a dummy variable, equal to one if the program became feasible to the student during Phase 1 and zero if it became feasible in Phase 2. *FirstEarlyOffer* is a dummy variable, equal to one if the program is the first to have become feasible to the student during Phase 1. *: $p < 0.1$; **: $p < 0.05$: ***: $p < 0.01$.

when entering Phase 2 (see Figure 3). They choose instead to stay in the procedure and are automatically removed at the beginning of Phase 2.

3.3 A University-Admissions Model with Learning and Regret

We now consider a simple model of university admissions that captures the key aspects of the DoSV. Particularly, we demonstrate that an early offer is accepted by students with a higher probability than later feasible offers.

Motivated by the direct evidence from our survey, we introduce a cost when a student learns about a university/program's quality. Moreover, we assume that students anticipate a feeling of regret when choosing a program that turns out to be worse than another program from which they received an offer. The notion of regret is based on the model by Loomes and Sugden (1982). In the same spirit as loss aversion, anticipated regret creates an asymmetry between the offer a student is holding and possible future offers. Thus, the model generates an endowment effect (Kahneman et al., 1990; for a survey, see Ericson and Fuster, 2014) with early offers as endowments.

The model has three periods, $t \in \{t_1, t_2, t_3\}$, as depicted in Figure 5, and a representative student. At the initialization period t_1, the student has already applied for admission to two universities, A and B, and university A has extended an early admission offer to the student. However, university B will only make its decision at t_3. Conditional on the information that the student has at t_1 or t_2, she expects that she will receive an offer from B with probability $p \in (0, 1)$. The student is required to rank both universities at t_2 and commit to accepting the top-ranked offer at t_3.

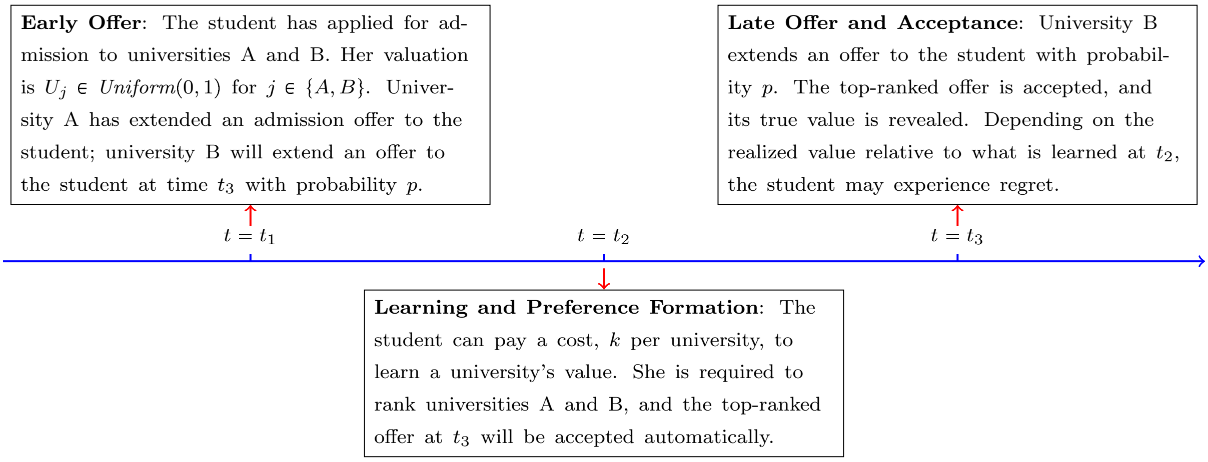


Figure 5: Timeline of University Admissions with Early Offers

At t_1, the student only knows that her valuations of the universities are i.i.d. draws from the uniform distribution, $U_j \in Uniform(0, 1)$, for $j \in \{A, B\}$. At t_2, the student can pay a cost, $k \in (0, 1)$, to learn a university's value, and she can decide to learn U_B after having learned U_A, or vice versa. Once the cost is paid for university j, she learns the realization of U_j. Moreover, at t_3, if the student accepts the offer from university j, she will discover U_j even if U_j is not learned at t_2. On the other hand, if she has not learned U_j at t_2 and does not accept j's offer at t_3, she will not learn U_j at t_3.

Decision-Making with Anticipated Regret. The student's decision-making follows utility maximization where the utility function is modified to capture regret. The student experiences *regret* in the following situation. At t_2 the student learns that $U_a = u_a$ and she submits a rank-order list with B above A. If B extends an admission offer to her, the student automatically accepts B at t_3 and learns its true value, say $U_B = u_B$. If $u_B \geqslant u_A$, she will enjoy B at its full value, u_B;[22] if $u_B < u_A$, she will regret and enjoy B's value at a discount, $u_B - r(u_A - u_B)$. The regret coefficient, r, is assumed to be in $(0, 1]$. The student does not regret if she accepts j at t_3 and does not learn the other university's value at t_2.

As $p \in (0, 1)$, it is always optimal to learn U_A if the student decides to learn about the universities at all. Going through the derivations detailed in Appendix B.1, we conclude that the student will optimally choose to learn U_A at t_2 if and only if

$$\mathbb{E}\left[\max\left\{\begin{array}{l} U_A(1-p) + p\max\{U_A, 0.5(1 - rU_A^2)\}, \\ U_A(1-p) + 0.5p(1 + U_A^2) - k \end{array}\right\}\right] - k > 0.5. \tag{3}$$

The left-hand side of Equation (3) contains an "$\mathbb{E}\max$" operator, because the student has the option to learn or not to learn U_B after having learned U_A. She will make the optimal decision conditional on the realization of U_A. Moreover, the left-hand side is monotonically decreasing in k; when $k \to 0$, it becomes strictly above 0.5; and when $k \to 1$, it falls strictly below 0.5. Therefore, there must exist $\bar{k}(p, r)$ such that Equation (3) becomes an equality when $k = \bar{k}(p, r)$. The student will learn U_A if and only if $k < \bar{k}(p, r)$. Clearly, $\bar{k}(p, r)$ is a function of p and r. To make the problem non-trivial, we make the following assumption.

Assumption 1. *The student always learns the value of university A: $k < \bar{k}(p, r)$.*

Essentially, the assumption requires that the learning cost k is low relative to the expected value of each university.

3.3.1 Optimal Learning Strategy in Period t_2

Conditional on the student having learned that $U_A = u_A$ and conditional on receiving an offer from B at t_3, the expected utility of top-ranking B without learning U_B is $\frac{1}{2} - \frac{r}{2}u_A^2$. Thus, the anticipated regret lowers the value of university B before U_B is learned.

[22] This rules out "rejoice" as defined in Loomes and Sugden (1982).

Following the derivations as detailed in Appendix B.1, we show that the optimal strategy at t_2 is to learn B's value if and only if

$$\min\left\{\sqrt{\frac{2k}{(1+r)p}}, \frac{\sqrt{1+r}-1}{r}\right\} < u_A < \max\left\{1-\sqrt{\frac{2k}{p}}, \frac{\sqrt{1+r}-1}{r}\right\}. \tag{4}$$

Intuitively, when u_A is high, there is no need to learn U_B, because accepting the offer or top-ranking A is optimal; when u_A is low, the student is willing to take the risk and top-rank B without learning U_B.

Define $\underline{u}_A \equiv \sqrt{\frac{2k}{(1+r)p}}$ and $\overline{u}_A \equiv 1-\sqrt{\frac{2k}{p}}$. To simplify Equation (4), we impose the following assumption.

Assumption 2. $\underline{u}_A < \frac{\sqrt{1+r}-1}{r} < \overline{u}_A$.

Assumption 2 is made mainly for expositional purposes and is not too restrictive. For instance, it holds true under the following two conditions: (i) $\underline{u}_A < \overline{u}_A$. This is satisfied when $\sqrt{\frac{2k}{p}} < \frac{1}{2}$. For a p close to one (i.e., the student is likely to receive an offer from university B) and a small k (i.e., a small learning cost), this inequality holds true. (ii) $\frac{\sqrt{1+r}-1}{r}$ is around $\frac{1}{2}$, which is satisfied for almost all $r \in (0,1]$.[23] We will revisit the consequences of relaxing this assumption.

Under Assumption 2, Equation (4) is simplified as

$$\underline{u}_A < u_A < \overline{u}_A. \tag{5}$$

We illustrate student behavior in Figure 6. Assumptions 1 and 2 are both satisfied in the figure where $k = 0.05$, $r = 0.1$, and $p = 0.9$. We show the expected utilities conditional on the realization of U_A, with and without learning U_B. The two curves divide the realizations of U_A into three segments: $[0, \underline{u}_A)$, $[\underline{u}_A, \overline{u}_A)$, and $[\overline{u}_A, 1]$.

We are interested in the probability of the student ranking A above B, or, equivalently, the probability that the student accepts A's offer conditional on holding both offers. We can characterize this probability in each of the segments of u_A.

(i) When $u_A \in [0, \underline{u}_A)$, ranking B above A without learning U_B is optimal, because u_A turns out to be low (cf. Equation 5) and accepting B when there is an offer from

[23] Note that $\frac{\sqrt{1+r}-1}{r}$ monotonically decreases in r for $r \in (0,1]$. It goes to 0.5 when $r \to 0$ and equals $\sqrt{2}-1 \approx 0.4142$ when $r = 1$.

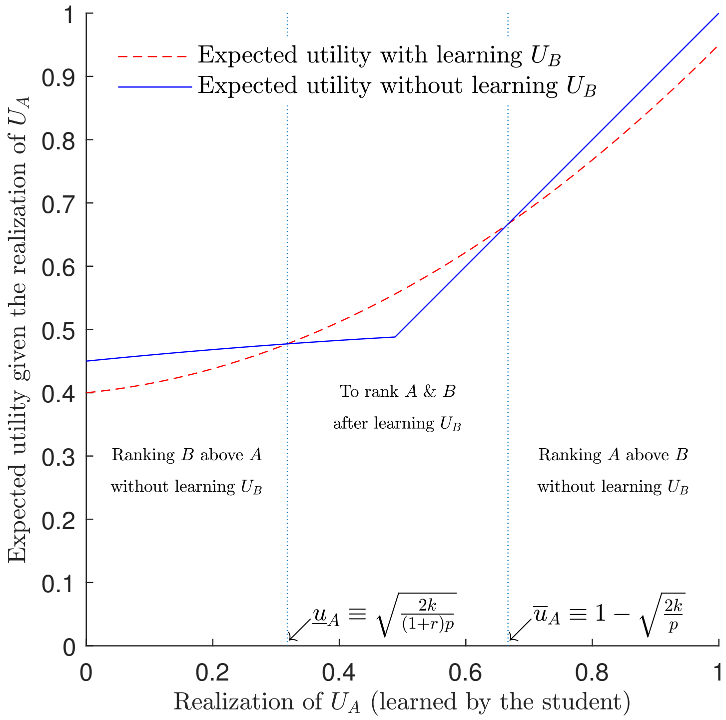


Figure 6: Expected Utility with/without Learning U_B Conditional on Having Learned U_A

Notes: In this figure, the learning cost is $k = 0.05$, the regret coefficient is $r = 0.1$, and the probability of receiving an offer from university B at t_3 is $p = 0.9$; Assumptions 1 and 2 are both satisfied. The solid line depicts the expected utility when the student does not learn U_B given the realization of U_A on the X-axis; the dashed line is the expected utility when the student learns U_B.

B leads to a higher expected utility even after the anticipated regret is taken into account ($0.5(1 - ru_A^2) \geqslant u_A$). From an ex ante point of view (at t_1), this happens with probability $\underline{u}_A$.

(ii) When $u_A \in [\underline{u}_A, \overline{u}_A)$, the student learns B's value and ranks the universities according to their realized values.[24] Given that $U_A = u_A$, before learning U_B, the probability of ranking A above B is u_A. From the view point at t_1, top-ranking A in this scenario happens with probability $(\overline{u}_A^2 - \underline{u}_A^2)/2$.

(iii) When $u_A \in [\overline{u}_A, 1]$, accepting A without learning U_B is optimal, because u_A turns out to be high enough (cf. Equation 5) and that accepting A leads to a higher expected utility than accepting B when there is an offer from B even after the anticipated regret is taken into account ($0.5(1 - ru_A^2) \geqslant u_A$). At t_1, this happens

[24] This also shows that the anticipated regret encourages the student to learn U_B. As the regret coefficient r increases, $\underline{u}_A = \sqrt{\frac{2k}{(1+r)p}}$, which is the lower bound of u_A for the student to learn U_B, decreases, while the upper bound does not depend on r. In other words, the interval of u_A in which the student learns U_B expands with r. For more discussion, see Lemma 1.

with probability $1 - \overline{u}_A$.

Taking the three cases together, from the perspective at t_1, the probability of ranking A above B is $\frac{1}{2} + \frac{rk}{(1+r)p} > \frac{1}{2}$. In other words, the student is more likely to rank A above B by a probability of $\frac{2rk}{(1+r)p}$.

3.3.2 Results from the Theoretical Model

The following proposition summarizes our main theoretical results.

Proposition 1. *When Assumptions 1 and 2 are both satisfied, ex ante (at t_1), the student top-ranks university A with probability $\frac{1}{2} + \frac{rk}{(1+r)p}$ and top-ranks university B with probability $\frac{1}{2} - \frac{rk}{(1+r)p}$. In the interior of the parameter space defined by Assumptions 1 and 2, she is more likely to rank A above B when*
(i) the cost of learning, k, is greater;
(ii) the regret coefficient, r, is higher; or
(iii) the probability of receiving an offer from university B, p, is lower.

The first statement of the proposition is a result of the detailed derivations in Section 3.3.1, while the comparative statistics are straightforward to compute. We therefore omit the formal proof.

The following lemma further emphasizes the importance of regret.

Lemma 1. *If there is no regret, $r = 0$, ex ante (at t_1), the student top-ranks university A or B with an equal probability, $\frac{1}{2}$, for all $k \in (0, 1)$ and $p \in (0, 1)$.*

The proof can be found in Appendix B.2. Note that when there is no regret, the intervals $[0, \underline{u}_A)$ and $[\overline{u}_A, 1]$ are symmetric in Figure 6. The lemma can also hold when there are heterogeneous learning costs such that it is less costly to learn about the quality of the first offer (results available upon request). At the same time, Lemma 1 highlights the importance of regret in our setting. Without regret, there is no early-offer effect.

Intuitively, taking Lemma 1 and Proposition 1 together, the anticipated regret pushes the student to learn U_B after having discovered that the value of A is relatively low, $u_A \in [\underline{u}_A, 1 - \overline{u}_A]$. If U_B turns out to be below u_A, A is accepted. By contrast, in the absence of the anticipated regret and a relatively low value of A, the student would simply accept B without learning its value U_B.

Robustness of Proposition 1. When Assumption 1 is satisfied but Assumption 2 is violated, Proposition 1 still holds true qualitatively, except that the expressions for the probabilities change. A special case is when $\underline{u}_A > \overline{u}_A$, or $\sqrt{\frac{2k}{(1+r)p}} > 1 - \sqrt{\frac{2k}{p}}$, such that it is never optimal for the student to learn U_B. A version of Figure 6 can be drawn with the two curves completely separated. In this case, the comparison between u_A and $\frac{1}{2} - \frac{r}{2}u_A^2$ (the expected value of accepting B conditional on the offer from B) determines the ranking behavior. That is, A is top-ranked if and only if $u_A > \frac{\sqrt{1+r}-1}{r}$, which happens with an ex ante probability of $1 - \frac{\sqrt{1+r}-1}{r} > \frac{1}{2}$ for all $r \in (0, 1]$.

The proposition and the lemma are robust to some ex ante heterogeneity in university quality, with some modification of interpretation. We assume that the university to extend the early offer is randomly selected, and the probability of ranking the first-offer university is averaged over the two possibilities of the identity of the first offer. Appendix B.3 provides a numerical example.

3.3.3 Comparison with DA

To highlight the advantages of the DoSV procedure, we now compare it with DA.

We introduce another period before t_1, which we denote by t_0. In period t_0, the student has decided to apply to both universities, A and B. Under DA, she is required to rank the universities at t_0 before receiving any offer. Moreover, at t_0, the probability that university A will extend an admission offer to the student is $p_A \in (0, 1]$; at time t_0, the distributions of U_A and U_B, the probability of an offer from university B, the learning technology, and the anticipated regret are the same as in period t_1. The earlier analysis of DoSV can be considered as conditional on the student having received an offer from A at t_1.

Proposition 2. *Evaluated at period t_0, the student always obtains a higher expected utility under DoSV than that under DA.*

The formal proof of this proposition is omitted, but a sketch is as follows. The student under DoSV can always adopt the same strategy at t_0 as under DA. Therefore, she can never do worse under DoSV. Moreover, under DA, the student loses the option to postpone learning until period t_2 when she has learned university A's admission decision. Under DoSV, she can decide to learn about A, B, or none of the programs once she knows university A's decision. This implies that the student is not always indifferent between

DA and DoSV. It should be emphasized that the welfare gain of DoSV in the presence of information costs holds true even when there is no regret.

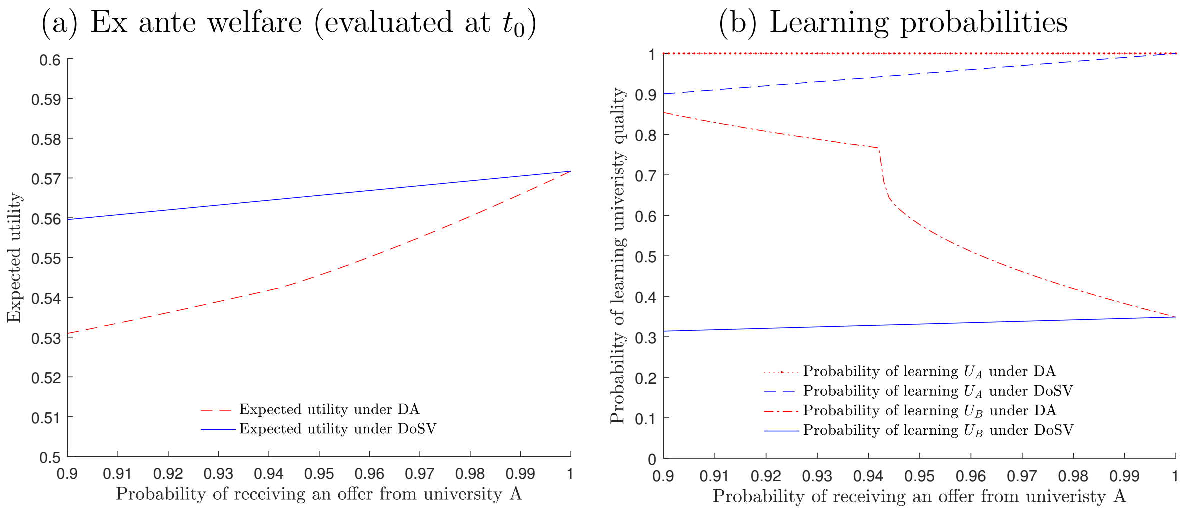


Figure 7: Welfare and Learning under DA and DoSV—A Numerical Example

Notes: In this figure, ex ante welfare is evaluated at t_0 before either of the universities makes an offer; the learning cost is $k = 0.05$, the regret coefficient is $r = 0.1$, and the probability of receiving an offer from university B at t_3 is $p = 0.9$, the same as in Figure 6; Assumptions 1 and 2 are both satisfied. The probability of receiving an offer from university A ranges from 0.9 to 1. In (a), ex ante welfare is calculated at the time point before universities A and B extend any offer. In (b), the student starts with learning U_A if she pays for learning; after learning U_A, she then decides to learn U_B or not.

As a numerical example, Figure 7 shows the comparison between DA and DoSV. Panel (a) depicts that DoSV dominates DA in terms of ex ante welfare (evaluated at t_0, before either university makes an offer). Not surprisingly, the two mechanisms achieve the same welfare level when $p_A = 1$, i.e., when the student is certain that she will receive an offer from university A.

The welfare loss under DA is mainly driven by the excessive learning about programs as illustrated by Figure 7(b). It shows that the probability of learning either university's quality is higher under DA than under DoSV even though the student may not receive offers from them.

To sum up this section, we provide evidence that allows us to narrow down the set of possible explanations of the early-offer effect. The findings from the data and the survey responses are consistent with students forming preferences over programs in the course of the procedure. Students need to collect information about the programs and are affected by regret that makes them value early offers more than later offers.

4 Implications for Market Design

Our explanation of the early-offer effect relies on costly learning about the programs. As the model demonstrates, the DoSV procedure is always preferable to the static implementation of DA with respect to minimizing information costs. Yet, the early-offer effect due to regret or other behavioral factors may imply that the arrival time of an offer affects admission outcomes and hence induces path dependency. In this section, we discuss how these two effects can be balanced.

We propose a novel hybrid design for matching markets in which agents find it costly to learn their own preferences. Such a hybrid design combines the advantages of both decentralization and centralization, while improving upon the DoSV procedure in Germany. Specifically, in contrast to DoSV it bundles the early offers to arrive only at certain points in time. Operating through an online clearinghouse, the hybrid mechanism contains the following stages:

(i) **Application**: Through the clearinghouse, students apply to a set of programs, without committing to any ranking of these program.

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

(iii) **Initial offers and communications**: On a pre-specified date, every program extends admission offers to its top-ranked applicants up to its capacity. Moreover, every program informs each of its applicants about the lowest rank among the admitted applicants as well as how she is ranked. This is automated by the clearinghouse.

(iv) **Subsequent offers and communications**: After a certain period of time, e.g., five days, students with offers are requested to hold at most one offer and decline the rest.[25] A student can choose to exit the clearinghouse without any offers or by accepting an offer. At the end of this period, each program with a certain number of rejected offers extends the same number of new offers to its top-ranked applicants among those who have never received its offer. The rank of the lowest

[25]If evidence shows that the decision to make a choice among the offers is difficult, one may allow a longer period and/or allow a student to hold two or more offers, while encouraging them to make a decision as early as possible.

ranked student among each program's admitted students is updated and shown to each applicant. There can be several periods like this sequentially.[26]

(v) **Final ranking**: On a pre-specified date, every student submits a ranking over the programs that she has applied to and has not rejected offers from.

(vi) **Final match**: With rankings from students and programs as well as the remaining seats at each program, the clearinghouse runs the DA mechanism and finalizes the matching.

The hybrid mechanism differs from DoSV in that it has a common date for every program to send out the initial offers as well as common dates for rounds of subsequent offers. The mechanism can be implemented thanks to modern information technology. Online clearinghouses are already used in practice not only in Germany, but among others for the high school match in New York City and university admissions in Australia, Brazil, China, and France (Parcoursup). Online communication between the clearinghouse and the applicants facilitates the decentralization in the stages of initial and subsequent offers.

The mechanism has several advantages. First and foremost, as in a decentralized market, it allows students to learn about the value of programs conditional on having received offers from them. Namely, with initial and subsequent offers, a student can start learning about the programs from which she already has offers. More generally, the student can update her offer probability at each program based on the feedback from the clearinghouse. Our empirical and theoretical results imply that this is more efficient since it avoids wasting time and effort on learning about programs that are unreachable.

Second, the hybrid mechanism enjoys the benefits of centralization due to the common date for initial and subsequent offers, the common date for the final rankings, and the common date for final offer acceptance. These restrictions speed up the matching process, and universities do not have to overbook to fill their seats.

Third, the common dates for initial and subsequent offers can mitigate the potential inefficiency caused by the early-offer effect, an improvement upon the DoSV. For example, universities may have incentives to behave strategically by sending offers early to certain applicants. This type of behavior is significantly limited by the mechanism.

[26] Note that this stage is similar to the dynamic version of university-proposing DA, as studied in a lab experiment by Klijn et al. (2019). Students can actively decide between offers at every step of DA. The experiments show that the dynamic university-proposing DA performs best with respect to payoffs and stability compared to its static counterpart and both versions of the student-proposing DA.

The proposed mechanism shares certain features with a dynamic implementation of university-proposing DA where students respond to offers in real time, following the protocol of DA. However, the proposed mechanism extends offers to students in bundles, and it can allow students to hold more than one offer over a certain period of time.

4.1 Matching Market Design in Practice

The hybrid mechanism differs from existing mechanisms, but combines the advantages of several forms of matching market designs in practice. We summarize the common designs in Table 8. There are six types (denoted D1–D6), from more decentralized to more centralized, each of which differs from our proposed mechanism in some way. Although we discuss general matching markets, we still use students/applicants and universities to refer to agents on the opposite sides.

In the most decentralized and uncoordinated design, type D1, there is no common date for initial offers, subsequent offers, or offer acceptances. Applicants never commit to a ranking over universities. This design is used for law clerk hiring in the U.S., a market suffering from unraveling (Avery et al., 2001). The labor market for fresh economics PhDs is also organized in this way. Given its decentralized nature, an applicant can defer learning about the quality of the university until she has received an offer, and thus reduce learning costs. However, a university can strategically choose when to make an offer and can set the deadline for offer acceptance, which opens up the possibility of unraveling.

Many decentralized markets manage to avoid unraveling by imposing a common date for offer acceptance, denoted by type D2 in Table 8. Examples include college admissions in the U.S., which have May 1 as the acceptance day, and graduate program admissions in the U.S., where April 15 is the common decision day. One problem is that the matching outcome is not guaranteed to be stable. As implied by our empirical results, another problem of type D2 is that universities can make early offers for strategic reasons.

The matching process is handled by a centralized clearinghouse in mechanisms of type D3. The leading example is university admissions in France, the Parcoursup procedure. An important feature of Parcoursup is that an applicant can hold at most one offer after a certain period of time following the receipt of multiple offers. This time limit, which is initially five days, is gradually reduced to a single day over the course of the procedure. This requirement speeds up the time that is needed to clear the market.

Table 8: Matching Market Designs in Practice

	Centralized?	Common offer dates: Initial	Common offer dates: Subsequent	Common date for final offer acceptance?	Applicant commits to a ranking?	Applicant holds multiple offers?	**Real-life Examples**	**Properties**
(D1)	No	No	No	No	No	Yes	Law clerks in the U.S.; labor market for fresh PhDs in economics.	It allows learning conditional on receiving offers, but the market can be prone to unraveling.
(D2)	No	No	No	Yes	No	Yes	College admissions in the US; graduate admissions in the US.	It allows learning conditional on receiving offers. Early offers can be made strategically, but the market is not prone to unraveling.
(D3)	Semi	No	No	Yes	No	Yes	University admissions in France (Parcoursup)	It is similar to (D2), except that it is run by a centralized clearinghouse.
(D4)	Semi	No	No	Yes	Yes (at the last stage)	Yes	University admissions in Germany (DoSV)	It is similar to (D3), except that students must commit to a ranking of universities on a given day.
(D5)	Yes	*Yes; one offer only.*		Yes	Yes (from the beginning)	No	Centralized school choice and college admissions; medical resident match in the U.S.	It does not allow learning conditional on receiving offers, but it is immune to unraveling and strategic early offers from the recruiting side.
(D6)	Yes	*Yes; one offer only.*		Yes	Yes (after the "trial" period)	No	Dynamic implementation of university admissions in Brazil and Inner Mongolia, China.	It is similar to (D5), except that it allows students to update their rankings over universities after obtaining information on offer probabilities in the "trial" period.
Our proposal		**Yes**	**Yes**	**Yes**	**Yes (at the last stage)**			

On the common date for final offer acceptance, an applicant keeps or rejects the single offer she has, and no more new offers will be made. One disadvantage of this design is that as in mechanisms of type D2, the matching outcome reached on the final day of offer acceptances is not guaranteed to be stable, since the procedure might stop before all students have received their best possible offer (Berry et al., 2019).

Type D4 is more centralized than type D3 in that, at a later stage of the process, it requires applicants to commit to a ranking of universities as inputs into the DA mechanism. The DoSV procedure for university admissions in Germany is a leading example. Relative to our proposed mechanism, DoSV does not have common dates for initial and subsequent offers, and therefore allows for the strategic timing of offers from the universities, especially if they have discretion over how to rank applicants.

Being completely centralized, type D5 includes the standard centralized school choice and college admissions as well as the medical resident match in the U.S. It requires every applicant to submit and commit to a ranking over universities at the beginning of the process. Then, the DA mechanism is run. As a key feature of centralized markets, each applicant receives at most one offer. Therefore, applicants cannot learn a program's quality conditional on having received an offer from it.

In mechanisms of type D5, it can be difficult for applicants to predict offer probabilities and thus costly to learn a program's quality based on these subjective probabilities. A recent innovation due to information technology is the dynamic implementation of centralized mechanisms, labeled D6 in Table 8. In university admissions in Brazil and Inner Mongolia, China, there is a "trial" period during which applicants submit rankings over universities without commitment. Meanwhile, everyone can modify her own ranking upon seeing her admission outcome given other applicants' current rankings. Therefore, an applicant may have a better assessment of offer probabilities and can concentrate on learning about those programs that are likely to make her an offer. However, in contrast to decentralized procedures, applicants in D6 can receive at most one offer.

Comparing the proposed hybrid mechanism with D1–D6, our mechanism is similar to a decentralized market in that an applicant can have multiple offers for some time. However, it is also more centralized, because initial and subsequent offers are sent out on pre-specified dates and because there is a common deadline for final offer acceptance. It is also similar to a centralized market, because it requires every applicant to commit to a ranking, but only at the last stage. Due to these features, our proposed mechanism enjoys the advantages of both centralized and decentralized mechanisms. Finally, it shares important features with the dynamic university-proposing DA which has been found to trump static and/or student-proposing DA with respect to stability (Klijn et al., 2019; Bó and Hakimov, forthcoming).

5 Conclusion

A recent trend in market design, in particular in the context of school choice and university admissions, is that matching markets are increasingly centralized into a single-offer procedure. Students are required to rank schools and universities from the outset. Theoretical justifications for this trend are usually formulated based on the assumption that agents know their own preferences and that their preferences are fixed over time.

Relying on a unique data set from Germany's university admissions, we provide clear evidence that students do not know their own preferences upon entering the matching procedure. Instead, the results are consistent with a model of students learning about universities at a cost, which is corroborated by direct survey evidence.

These results have direct implications for matching market design. Regarding the trend of centralizing matching markets, our results provide a cautionary tale and call for a balance between centralization and decentralization. In a decentralized market, an agent can receive match offers over time and can hold multiple offers, which facilitates sequential learning about potential match partners. Our proposed hybrid design integrates this feature into a centralized design. The hybrid design does not require agents to commit to a ranking over their potential match partners until a late stage. Moreover, offers arrive on pre-announced dates, allowing agents to more efficiently invest in learning conditional on the offers that have arrived while restricting the scope for strategic behavior by the universities.

We theoretically show that this hybrid design dominates the common implementation of the DA mechanism. Its advantages become more important as market segments are increasingly integrated. For example, charter and traditional public schools are in a single centralized matching procedure in Denver and New Orleans. In such markets, an agent can face a large number of potential match partners. Learning costs can cause substantial inefficiency if every agent has to commit to a ranking over potential match partners at the beginning of the matching procedure.

The hybrid design can be implemented by an online clearinghouse, similar to what is in practice in Germany and France's university admissions. The fact that students and universities can "interact," such as students receiving or rejecting admission offers from universities during the procedure, also brings the benefit of increased transparency of the procedure. How large the benefit can be is a question that we leave for future research.

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Appendix to

Decentralizing Centralized Matching Markets: Implications from Early Offers in University Admissions

Julien Grenet   Yinghua He   Dorothea Kübler

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List of Appendices

Appendix 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, postcode), 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 only available for approximately 50 percent of the applicants but, as explained in Section A.1.2 below, it can be inferred for a large fraction of those for whom the information in 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 formal 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—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 universities, including all quotas. So-called pre-selection quotas are filled before the other quotas and are typically applied to 10–20 percent 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 percent 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 percent of the seats as well. Finally, the University Selection Quota (*Auswahlverfahren der Hochschulen*) tends to apply to around 60 percent 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 universities 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 only available for 49.6 percent of applicants. However, this information can be inferred for a large fraction of the other applicants based on how they are ranked under the programs' *Abitur* quota, these rankings being strictly determined by an applicant's *Abitur* grade. The latter 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 discrete scale of the *Abitur*, missing grades can be imputed without error in the following cases: (i) when an applicant is ranked above any applicant with a grade of 1.0 (in which case the assigned grade is 1.0); (ii) when 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) when 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 missing information in the data, bringing the overall proportion of students with a non-missing *Abitur* grade to 83 percent.

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

Feasible programs. A program is defined as being ex post feasible for 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 socio-demographic or postcode 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 only consider students who applied to two feasible programs and who either actively accepted an early offer in Phase 1 or were automatically assigned to their best offer 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 application and admission 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 percent completed the survey in July and August while 48 percent 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 collection 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?
    - 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 order? [Rate on a Likert scale]

    - I had a clear ranking with respect to my preferences.
    - I did not have a clear ranking since I still needed to collect information in order to rank my applications according to my preferences.
    - I did not have a clear ranking since 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]

Appendix B Model: Proofs and Additional Results

This appendix provides more details on the model described in Section 3.3.

B.1 Derivations of the Decision-Making Process in Period t_2

Specifically, the student's expected utilities in different cases are as follows:

(i) If the student does not learn U_A or U_B, she randomly chooses a ranking of the two universities and receives an expected payoff of 1/2. No regret will occur in this case.

(ii) It can be shown that it is always better to learn U_A first, if the student decides to learn any value. If she has paid the cost and learned university A's value, say $U_A = u_A$, she has to decide whether she will learn U_B.

- If yes, she learns B's value and ranks the two universities according to their observed values; in this case, her expected payoff at t_1, conditional on $U_A = u_A$ and net of the cost, is

$$u_A(1-p) + p\mathbb{E}[\max\{u_A, U_B\}] - k = u_A(1-p) + 0.5p(1+u_A^2) - k.$$

- If not, the regret may come into play. Her expected utility at t_1 conditional on u_A is

$$\begin{aligned} &u_A(1-p) + p\max\left\{ u_A, \begin{array}{l} \mathbb{E}(U_B|U_B \geqslant u_A)\mathbb{P}(U_B \geqslant u_A) \\ +\mathbb{E}((1+r)U_B - ru_A|U_B < u_A)\mathbb{P}(U_B < u_A) \end{array} \right\} \\ =&u_A(1-p) + p\max\{u_A, 0.5(1-ru_A^2)\} \end{aligned}$$

- The optimal strategy at t_1, conditional on having learned $U_A = u_A$, is to learn B's value if and only if

$$u_A(1-p) + p\max\{u_A, 0.5(1-ru_A^2)\} < u_A(1-p) + 0.5p(1+u_A^2) - k. \quad \text{(A.1)}$$

(iii) In summary, the student will optimally choose to learn U_A at t_1 if and only if

$$\mathbb{E}\left[\max\left\{\begin{array}{l} U_A(1-p) + p\max\{U_A, 0.5(1-rU_A^2)\}, \\ U_A(1-p) + 0.5p(1+U_A^2) - k \end{array}\right\}\right] - k > 0.5,$$

which is exactly Equation (3) in the main text.

B.2 Proof of Lemma 1

We now have $r = 0$. The student's expected utilities in different cases are as follows:

(i) If the student does not acquire any information, she randomly chooses a ranking of the two universities and receives an expected payoff of 1/2.

(ii) If she has learned university A's value, say $U_A = u_A$, she must decide whether to learn the value of university B, U_B.

- If yes, she learns B's value and ranks the two universities according to their observed values; in this case, her expected payoff at t_1, conditional on $U_A = u_A$ and net of the cost, is

$$u_A(1-p) + p\mathbb{E}[\max\{u_A, U_B\}] - k = u_A(1-p) + 0.5p(1+u_A^2) - k.$$

- If not, her expected payoff at t_1 conditional on u_A is

$$u_A(1-p) + p\max\{u_A, \mathbb{E}(U_B)\} = u_A(1-p) + p\max\{u_A, 0.5\}$$

- The optimal strategy at t_1, conditional on having learned $U_A = u_A$, is to learn B's value if and only if $k < 0.5p(1+u_A^2) - p\max\{u_A, 0.5\}$.

(iii) The student will optimally choose to learn U_A at t_1 if and only if

$$\mathbb{E}\left[\max\left\{\begin{array}{l} U_A(1-p) + p\max\{U_A, 0.5\}, \\ U_A(1-p) + 0.5p(1+U_A^2) - k \end{array}\right\}\right] - k > 0.5. \tag{A.2}$$

For all k and p such that Equation (A.2) is violated, the student does not learn anything and top-ranks each university with an equal probability. Lemma 1 is thus satisfied.

For all k and p such that Equation (A.2) is satisfied, the student optimally learns U_A, say $U_A = u_A$. There are two cases.

Case 1: $k < 0.5p(1+u_A^2) - p\max\{u_A, 0.5\}$ is violated for all $u_A \in [0, 1]$. This implies that the student will optimally choose not to learn U_B and top-rank A if and only if

$u_A > 0.5$. At t_0, this happens with probability 0.5. Lemma 1 is thus satisfied.

Case 2: $k < 0.5p(1 + u_A^2) - p\max\{u_A, 0.5\}$ is satisfied for some $u_A \in [0, 1]$. We can follow Section 3.3.1 and show that the ex ante probability of top-ranking A is 0.5, which proves the lemma.

B.3 Heterogeneous Universities

This appendix considers that the two universities are heterogeneous.

We modify the model in Section 3.3 by introducing two states of the world. In the first state, at t_1 and t_2, $U_A \in Uniform(0, 1)$ and $U_B \in Uniform(\Delta, 1 + \Delta)$ for $\Delta \in (0, 0.5)$. In the second state, at t_1 and t_2, $U_A \in Uniform(\Delta, 1 + \Delta)$ and $U_B \in Uniform(0, 1)$. All other aspects of the model remain the same.

Each state happens with probability 0.5, and at t_0 and t_1, the student already knows which state she is in. We are interested in the early-offer effect on the probability of accepting university A, averaging over the two states. Specifically, we calculate the probability of accepting A in the first state and then the one in the second state. We thus obtain the average probability of accepting university A. Similarly, we obtain the average probability for university B. The difference between the two averages is the early-offer effect.

With the parameter values in Figure 6 as the benchmark ($k = 0.05, r = 0.1, p = 0.9$), Table B1 shows the early-offer effect on the probability of accepting A, the first-offer university.

For a wide range of heterogeneities, $\Delta = 0.05, 0.10, \ldots, 0.50$, column 1 shows that in the benchmark case, the student is more likely to accept the early offer, with an extra probability ranging from 0.25 to 0.5 percentage points. When the probability of receiving a second offer decreases (column 2), the early offer has a larger effect. Similarly, the effect increases when the student has a larger regret coefficient (column 3) or a higher learning cost (column 4). Although Proposition 1 considers homogeneous universities, the comparative statistics in the proposition are consistent with the patterns in Table B1.

Table B1: Early-Offer Effects (in Percentage Points) on Offer Acceptance Probability—Heterogeneous Universities

Heterogeneity in university quality Δ	Benchmark case $k = 0.05$ $r = 0.1$ $p = 0.9$ (1)	Lower offer prob. $k = 0.05$ $r = 0.1$ $\boldsymbol{p = 0.8}$ (2)	Larger regret coeff. $k = 0.05$ $\boldsymbol{r = 0.15}$ $p = 0.9$ (3)	Higher learning cost $\boldsymbol{k = 0.1}$ $r = 0.1$ $p = 0.9$ (4)
0.05	0.50	0.57	0.72	1.01
0.10	0.50	0.57	0.72	1.01
0.15	0.50	0.57	0.72	1.01
0.20	0.50	0.57	0.72	1.01
0.25	0.50	0.57	0.72	1.01
0.30	0.50	0.57	0.72	1.01
0.35	0.25	0.35	0.36	1.01
0.40	0.25	0.28	0.36	1.01
0.45	0.25	0.28	0.36	1.00
0.50	0.25	0.28	0.36	0.50

Notes: This table studies a model that introduces heterogeneous universities into the model in Section 3.3. It has two states of the world. In the first state, at t_1 and t_2, $U_A \in \mathit{Uniform}(0, 1)$ and $U_B \in \mathit{Uniform}(\Delta, 1 + \Delta)$ for $\Delta \in (0, 0.5)$. In the second state, at t_1 and t_2, $U_A \in \mathit{Uniform}(\Delta, 1 + \Delta)$ and $U_B \in \mathit{Uniform}(0, 1)$. All other aspects of the model remain the same. For a range of university quality heterogeneity Δ and a configuration of parameters (learning cost k, regret coefficient r, and second offer probability p), each column presents the early-offer effect which is the excess probability of accepting the earlier offer. Column 1 is the benchmark case, and in each of columns 2–4, one of the parameters, (p, r, k), changes.

Appendix C Supplementary Figures and Tables

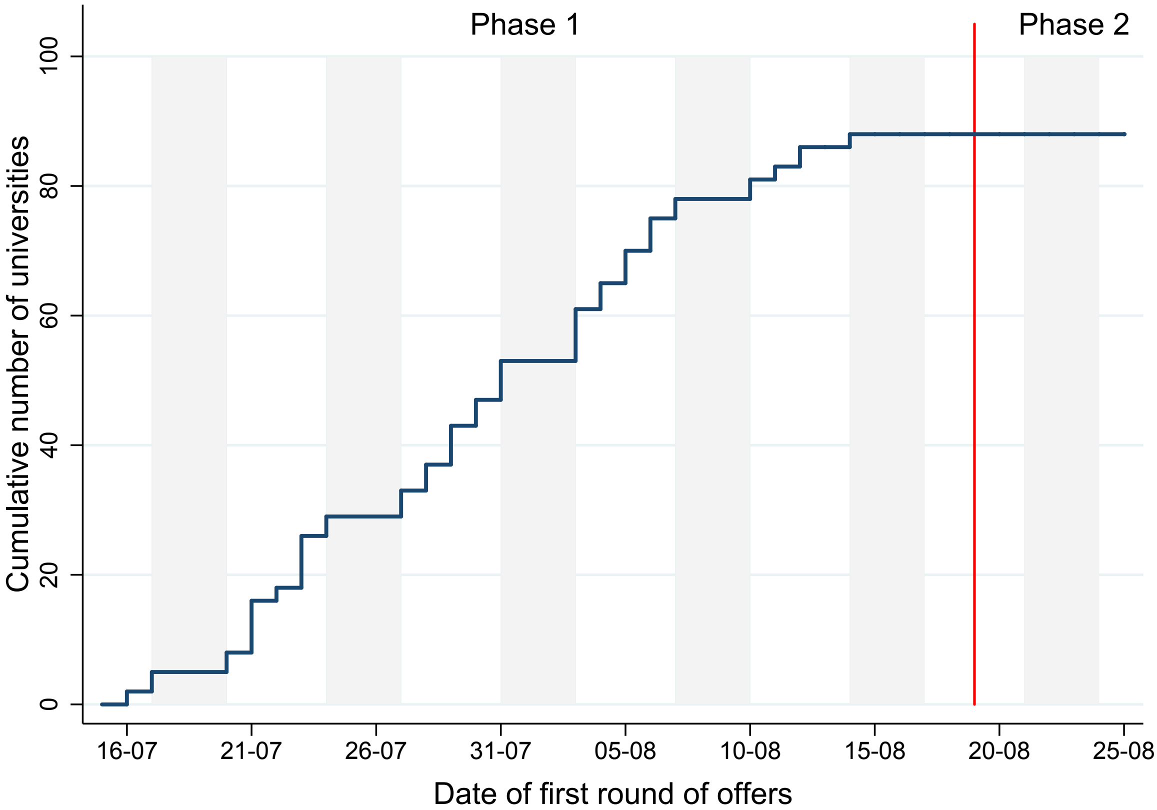

Figure C1: First Round of Offers Sent Out by Universities

Notes: This figure shows the cumulative number of universities 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 universities—are denoted by gray shaded areas.

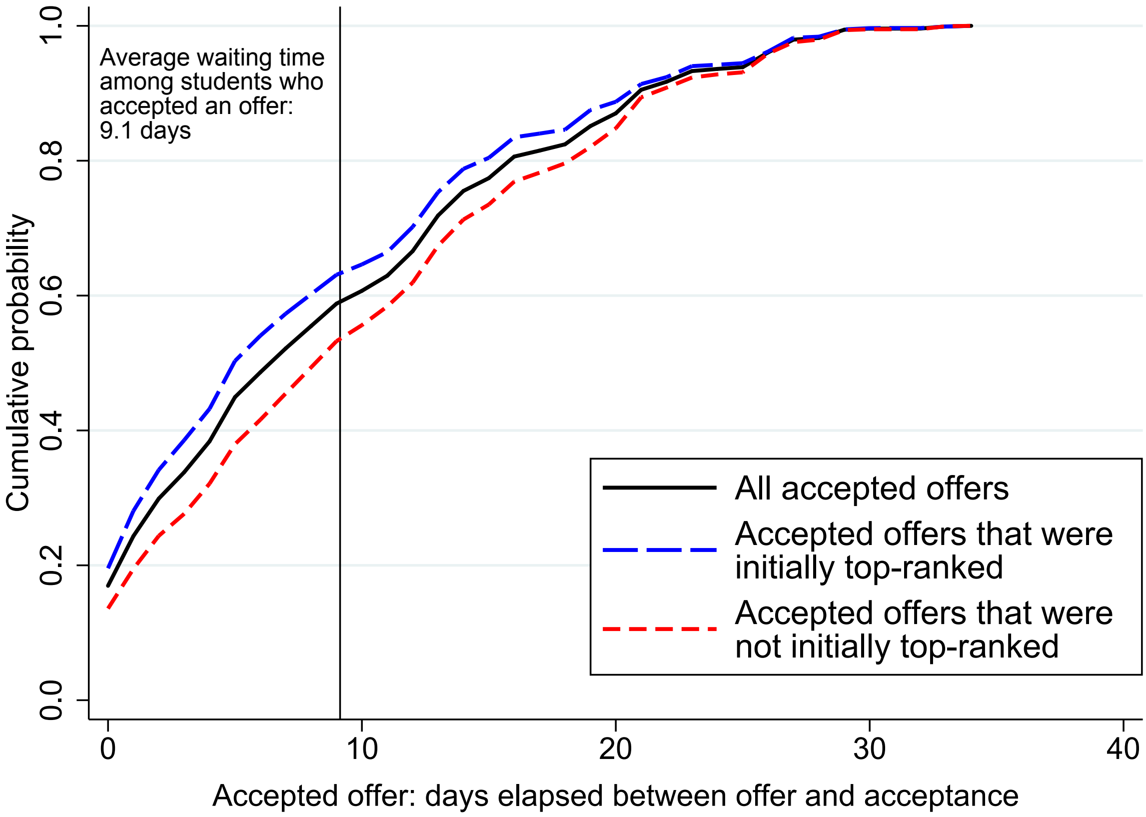

Figure C2: Accepted Offer: Cumulative Distribution of Number of Days Elapsed between Offer and Acceptance—Students who Applied to at Least Two Feasible Programs and Accepted an Offer

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 who either actively accepted an early offer during Phase 1 or were automatically assigned to their best offer 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).

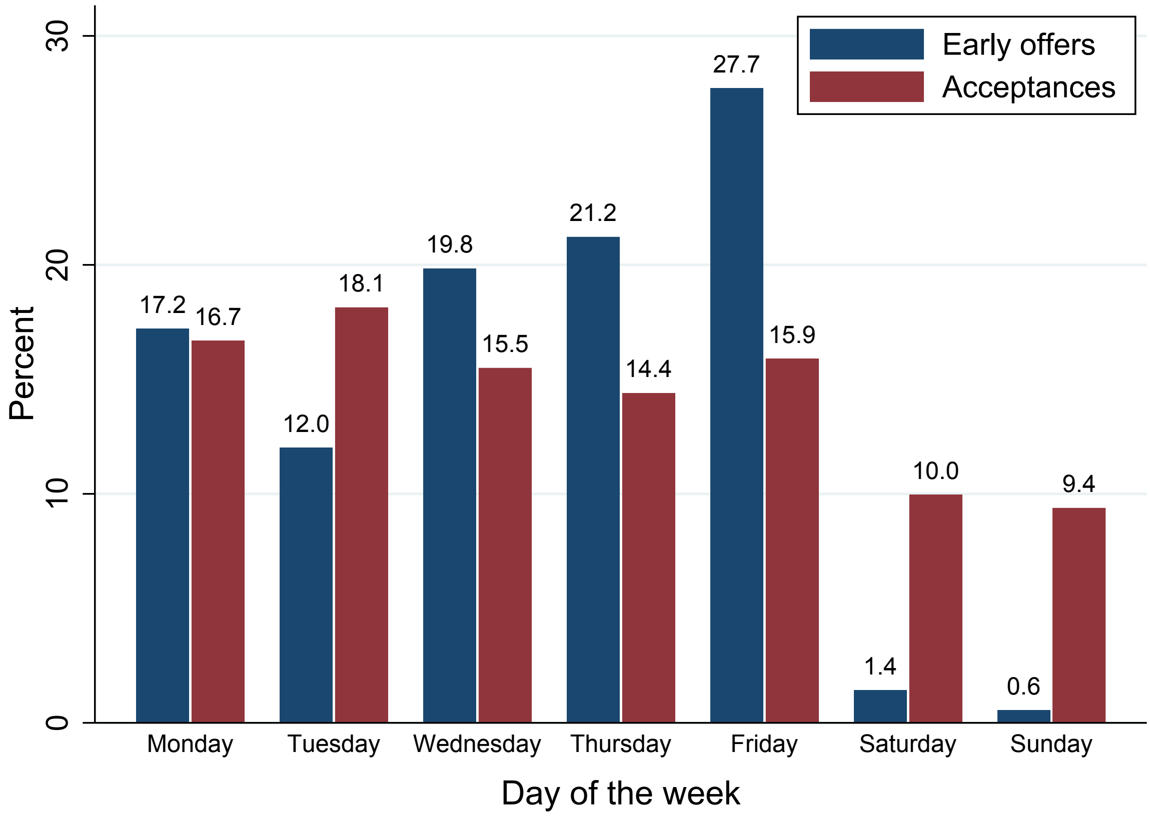

Figure C3: Distribution of Early Offers and Acceptances across the Days of the Week

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 C2: 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 (in thousand km)			−9.35***	−9.36***	−9.36***
			(0.33)	(0.33)	(0.33)
Distance to university (in thousand km) – 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 0 and 1)				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
Number of feasible programs	66,263	66,263	66,263	66,263	66,263

Notes: This table reports the estimates from a conditional logit model for the probability of accepting an offer from a feasible program. The sample only includes students who applied to at least two feasible programs and who either actively accepted an early offer during Phase 1 or were automatically assigned to their best offer in Phase 2. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., to the programs from which she could have received an offer by the end of Phase 2. *EarlyOffer* is a dummy variable, equal to one if the program became feasible to the student during Phase 1 and zero if it became feasible in Phase 2. *FirstEarlyOffer* is a dummy variable, equal to one if the program is the first to have become feasible to the student during Phase 1. *: p <0.1; **: p <0.05: ***: p <0.01.

Table C3: Acceptance among Feasible Programs and Final ROLs—Controlling for How Students Initially Rank Programs

	Acceptance among feasible (conditional logit) (1)	Final ROL (rank-order 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 (in thousand km)	−6.54***	−6.35***
	(0.39)	(0.38)
Distance to university (in thousand km) – 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 0 and 1)	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
Number of feasible programs	66,263	66,263

Notes: Column 1 reports the estimates from a conditional logit model for the probability of accepting an offer from a feasible program. Column 2 reports estimates from a rank-order logit model for the probability of observing a student's final rank-order list (ROL) of feasible programs. The sample only includes students who applied to at least two feasible programs and who actively accepted an early offer during Phase 1 or were automatically assigned to their best offer in Phase 2. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., to the programs from which she could have received an offer by the end of Phase 2. Final ROLs are constructed as follows: (i) when a student actively accepted an early offer during Phase 1, we only assume that she prefers the accepted offer to all other feasible programs in her ROL; (ii) when a student was assigned to a program in Phase 2, we use as her final ROL the partial order of feasible programs in the ROL that the student submitted in Phase 2, up to the first program that made her an early offer in Phase 1—programs ranked below this highest ranked early offer are only assumed to be less preferred than those ranked above (their relative rank order is ignored). *EarlyOffer* is a dummy variable, equal to one if the program became feasible to the student during Phase 1 and zero if it became feasible in Phase 2. *FirstEarlyOffer* is a dummy variable, equal to one if the program is the first to have become feasible to the student during Phase 1. *: $p < 0.1$; **: $p < 0.05$: ***: $p < 0.01$.

Table C4: Initial vs. Final Ranking of Feasible Programs—Students who submitted an initial ROL that they actively chose

	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	−0.083**	−0.068	−0.073	0.476***	0.437***	0.499***
	(0.041)	(0.042)	(0.119)	(0.065)	(0.068)	(0.178)
FirstEarlyOffer: First offer in Phase 1		−0.041	−0.027		0.076*	0.104***
		(0.026)	(0.026)		(0.039)	(0.040)
Distance to university (in thousand km)			−5.03***			−9.50***
			(0.32)			(0.53)
Distance to university (in thousand km) – squared			6.35***			11.84***
			(0.53)			(0.87)
Program is in student's region (*Land*)			0.010			0.033
			(0.041)			(0.063)
Program's ranking of student (between 0 and 1)			−0.021			0.106
			(0.266)			(0.431)
Chances of not receiving an offer from program in Phase 2			0.018			0.057
			(0.086)			(0.126)
Program fixed effects (376)	Yes	Yes	Yes	Yes	Yes	Yes
Number of students	6,953	6,953	6,953	6,953	6,953	6,953
Number of feasible programs	24,724	24,724	24,724	24,724	24,724	24,724

Notes: This table reports estimates from a rank-order logit model for the probability of observing a student's initial and final rank-order list (ROL) of feasible programs. The sample only includes students who applied to at least two feasible programs, who submitted an initial ROL that they actively chose (i.e., before Phase 1), and who actively accepted an early offer during Phase 1 or were automatically assigned to their best offer in Phase 2. Each student's choice set is restricted to the feasible programs that she included in her initial ROL, i.e., to the programs from which she could have received an offer by the end of Phase 2. Columns 1–3 consider students' initial ROL while columns 4–6 consider their final ROL. We take as a student's initial ROL the partial order of feasible programs that she ranked at the beginning of Phase 1. The final ROL is constructed as follows: (i) when a student actively accepted an early offer during Phase 1, we only assume that she prefers the accepted offer to all other feasible programs in her ROL; (ii) when a student was assigned to a program in Phase 2, we use as her final ROL the partial order of feasible programs in the ROL that she submitted in Phase 2, up to the first program that made her an early offer in Phase 1—programs ranked below this highest ranked early offer are only assumed to be less preferred than those ranked above (their relative rank order is ignored). *EarlyOffer* is a dummy variable, equal to one if the program became feasible to the student during Phase 1 and zero if it became feasible in Phase 2. *FirstEarlyOffer* is a dummy variable, equal to one if the program is the first to have become feasible to the student during Phase 1. *: $p<0.1$; **: $p<0.05$: ***: $p<0.01$.

Table C5: 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 0 and 1)	0.270	−0.369*
	(0.182)	(0.162)
Distance to university (in thousand km)	4.99***	15.91***
	(1.31)	(1.10)
Distance to university (in thousand km) – 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 an 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 who actively accepted an early offer in Phase 1. The sample in column 2 further includes students who were automatically assigned to their best offer 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.

[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.