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College Application Choices in a Repeated Deferred Acceptance (DA) Setting: Empirical Evidence from Croatia*

Abstract

How do beliefs on admission probability influence application choices? In this study, we empirically investigate whether and how admission probability is reflected in application choices in a centralized admission system. We exploit a novel setting of a dynamic deferred acceptance mechanism as employed in Croatia with hourly information updates and simultaneous application choices. This setting allows us to explore within-applicant strategic adjustments as a reaction to changing signals on admission probability. We show in an RDD analysis that applicants react to negative signals on admission probability with an increased propensity to adjust their application choices by 11-23%. Additionally, we show how application strategies evolve over time, while applicants learn about their admission probability. The group most-at-risk to remain unmatched improves their application choices by applying to programs with a higher admission probability towards the application deadline. Yet, we also identify a popular and potentially harmful strategy of applying to safer programs before applying to more risky "reach" programs. About a quarter of applicants have the potential to improve their application choices by resorting their application choices.

Keywords: belief updating, college admission, deferred acceptance, higher education, preference misrepresentation

JEL classification: D82, I21, I23

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1 Introduction

The decision of where and what to study strongly influences future income prospects (Altonji et al., 2014). Consequently, poor college application choices can have detrimental long-run consequences. One factor contributing to poor application choices are information frictions (Bettinger et al., 2012; Dynarski et al., 2021; Hoxby and Turner, 2015). Removing such frictions can support students in making better application choices and ultimately gain admission to a study program that suits their interests and abilities. Centralized application systems mitigate information frictions by offering easily accessible information on program characteristics, admission criteria and often a proxy for admission probability. Still, it remains unclear whether applicants are able to correctly process this information, thereby making better application choices.

According to the canonical school choice model by Abdulkadiroğlu and Sönmez (2003), applicants in a centralized admission system based on a Deferred Acceptance (DA) algorithm fare best when ranking their application choices according to their true preferences. Yet, a growing literature shows that applicants incorporate admission probability in their choices and thus misrepresent their preferences. For one part, this can be explained with biased beliefs on admission probability. Applicants over- or underestimate their admission chances (Arteaga et al., 2022; Larroucau et al., 2024) and consequently apply to too few programs or omit feasible programs from their application. For another part, applicants deviate from classical fully rational preferences, signaling a preference for study programs with higher admission probability but lower returns (Artemov et al., 2020; Hakimov and Kübler, 2021; Hassidim et al., 2021; Shorrer and Sóvágó, 2024). While the former bias can be addressed by providing more accurate information about admission probabilities, the latter behavior persists and may lead to significant application mistakes that result in a sub-optimal admission outcome.

In this study, we investigate how beliefs on admission probability shape application strategies, how applicants react to information on admission probability and whether more accurate information encourages strategic adjustments. We exploit the unique setting of a dynamic DA mechanism that is employed to assign applicants to study programs in Croatia. Here, applicants observe a proxy for admission probability in the form of preliminary admission outcomes for all ranked programs. At each full hour, these preliminary admission outcomes are updated based on revised application choices. Compared to the proxy on admission probability provided in other (static) systems, the proxy provided in Croatia can be regarded as more informative as it is based on application choices and competition of the current cohort. Yet, the proxy fluctuates as a result of each applicants' own and their competitions' adjustments of the application choices and should thus be regarded as a fuzzy signal on admission probability. This setting allows us to investigate within-applicants adjustments of the application strategy to fluctuating signals on admission probability.

In the first part of our study, we explore the dynamic nature of the Croatian system, which distinguishes it from the more commonly applied static system. We show that the admission cutoff of most programs declines over time, making it easier to be admitted at the application deadline than the prior signals on admission probability indicate. The cutoff score of the average program fluctuates in about 30% of hours by 3.45 points. The cutoff score of larger programs fluctuates more frequently, which is driven by the larger number of applicants above the cutoff whose adjustments induce a cutoff score fluctuation. Meanwhile, the magnitude of fluctuations decreases in the programs' quota. These fluctuations are driven by adjustments of application choices, which are most frequent right after the first preliminary admission outcomes are published and towards the application deadline.

In the second part of our study, we leverage a Regression-Discontinuity-Design (RDD) based on sharp (preliminary) admission cutoffs to show that applicants consider their beliefs on admission probability in their application choices. Applicants start the application process with their initial beliefs on admission probability and update their beliefs to the signals they receive. The strongest signal for admission probability is whether applicants are tentatively above or below the sharp admission cutoff. Thus, we consider applicants above the cutoff as receiving a positive signal, while applicants below the cutoff receive a negative signal on admission probability. As cutoff scores fluctuate, admission probability for applicants just around the admission cutoff is highly comparable. This implies that adjusting the application choices as a response to a negative signal is not justified by a lower admission probability. Still, we observe that applicants who receive a negative signal on admission probability have a 11-23% higher probability to adjust their application choices. In particular, we find that when applicants receive a negative signal, the probability that they omit the affected program from their application is 8-14% higher compared to applicants who receive a positive signal. This shows that beliefs on admission probability are influenced by the information signal and shape application choices.

In the third part, we broaden our analysis from one program to the full application strategy, that is, the composition and ordering of study programs in the application choices. We investigate how admission probability is reflected in the application strategy and whether this changes over time. To this end, we compute a measure of admission probability for each applicant and program by simulating admission cutoffs for random samples of applicants. Based on this applicant $\times$ program specific measure we determine for each hourly application strategy each applicants' risk of not being admitted to any ranked program. In each cohort, 8-14% of applicants have a particularly high initial risk to remain unmatched. As they start receiving information signals on admission probability, this group of applicants manages to reduce this risk by up to 20 pp. They achieve this by swapping programs with a low admission probability for programs with a higher admission probability, rather than by extending their (relatively short) rank-ordered list (ROL) of study programs. The large majority of applicants has a particularly low initial risk to remain unmatched of only 0-1%. Although this risk remains low, also these applicants adjust their application strategy with respect to admission probability. While initially they ranked more risky "reach" programs in the top-3 positions, this quickly changes as they receive signals on admission probability. At the application deadline, they rank programs with a higher admission probability on the top-3 ranks and more risky programs on the lower ranks. Under the assumption that applicants have a preference for competitive programs, which is supported by the initial application choices, this contradicts the theory of optimal application strategies (Abdulkadiroğlu and Sönmez, 2003; Ali and Shorrer, 2025), according to which the ranked programs should be ranked according to one's true preferences. Yet, this behavior has also been observed in experiments (Y. Chen and Sönmez, 2006; Pais and Pintér, 2008) and fits the behavioral concept of expectation-based loss-aversion (Dreyfuss et al., 2022).

Additionally, we combine the application data with survey data on applicants' reported top-3 most preferred programs and expected admission probability thereto to investigate whether beliefs on admission probability are reflected in the initial application choices. In the previous exercise we had to assume that applicants have a preference for more competitive programs and correctly assess their admission probability. Now, we observe applicants true preferences and their subjective beliefs on admission probability and can compare these to their initial application choices prior receiving any signal on their admission chances. While about 30% of applicants apply according to their reported true preferences, 17% of applicants rank none of their reported true preferences in their initial application choices. These strategies are strongly related to applicants' expected risk of not being admitted to any of their top-3 truly-preferred programs. Among the group with a particularly high expected risk, the share of applicants who do not rank any of their true preferences is significantly higher, at 40%. Meanwhile, 35% of applicants in the group with a particularly low expected risk rank their initial application choices according to their true preferences. Additionally, subjective beliefs on admission probability are reflected in the initial application choices of 26% of applicants. Of those, more than 80% omit programs for which they expect admission probability to be lower. This shows that already in the initial application choices applicants misrepresent their preferences. In particular, they do so by omitting programs with a lower expected admission probability. In the dynamic system the initial application choices are not binding. Thus, applicants have no reason to omit any of their most preferred study programs, even if they expect admission probability to be low. The cost of this application strategy is a missed opportunity of receiving an information signal and, thus, learning about their true admission probability.

In the last part of our study, we investigate whether the observed application strategies, i.e., sorting by admission probability and omitting programs with a low admission probability, are consequential for applicants' admission outcome. To this end, we simulate two counterfactual scenarios by replicating the assignment mechanism based on alternative application choices. For the first simulation we resort applicants final set of applications by admission probability in ascending order such that they apply to risky programs first. By that, we assume that applicants have a preference for the most competitive ranked program. Comparing the simulated and observed admission outcome we find that about a quarter of applicants could be admitted to a more competitive program, simply be resorting their applications. For the second simulation we compose counterfactual applications from the ten most competitive programs an applicant ever considers to assess the consequence of omitting programs with lower admission probabilities. In this counterfactual scenario, 13% of applicants are admitted to a more competitive program compared to the observed admission outcome. Yet, the share of applicants who are not admitted at all is 18 pp higher than in the observed scenario. In line with portfolio choice (Ali and Shorrer, 2025), this shows that applying only to the most preferred but also most risky programs is not necessarily an optimal strategy in a constrained choice setting.

Overall, we show that beliefs on admission probability are reflected in application choices. We identify two popular strategies, a) omitting programs with a low(er) admission probability and b) sorting ranked programs by admission probability. The former strategy keeps applicants from learning about their true admission probability in the beginning of the adjustment period and from being admitted to a potentially feasible program at the application deadline. The latter strategy results in applicants being admitted to less-competitive than possible programs and could be corrected at no risk. Similar application strategies are attributed in the literature to a behavioral bias referred to as expectation-based loss aversion (Dreyfuss et al., 2022; Kleinberg et al., 2024; Meisner and Von Wangenheim, 2023). Whether the Croatian setting enhances this behavioral bias remains to be investigated.

The Croatian system is unique in its' way of providing up-to-date and applicant-specific information on admission probability. We show that applicants overreact to this information as they adjust their application choices to negative signals besides strictly positive admission probabilities. This is true in particular since admission cutoff scores decline over the adjustment period, implying that omitting a program in response to an early negative signal may result in applicants not applying to preferred and (unexpectedly) feasible programs. Thus, although applicants in Croatia are more informed than applicants in the more commonly applied static system, the fluctuating signal on admission probability cannot fully eliminate information bias due to applicants misinterpreting the information. Yet, we also show that applicants who initially make the most risky choices improve their application choices over time. On them, the information signal seems to have the desired information-bias-correcting effect.

With our research we contribute to three strands of literature. First, we contribute to the literature that demonstrates a gap between theoretically optimal and observed application strategies in strategy-proof school choice mechanisms. According to the canonical school choice model by Abdulkadiroğlu and Sönmez (2003), applicants in a strategy-proof school choice mechanism should always apply according to their true preferences. Although strategy-proofness dissolves when applicants are constrained in the number of programs they are allowed to rank (Calsamiglia et al., 2010; Haeringer and Klijn, 2009), it remains an optimal strategy to rank the constrained set of selected programs according to one's true preferences (Ali and Shorrer, 2025). Yet, experimental (see Hakimov and Kübler, 2021 for an overview of laboratory experiments; L. Chen and Pereyra, 2019; Rees-Jones and Skowronek, 2018; Ye, 2023) and empirical evidence (Artemov et al., 2020; Hassidim et al., 2021; Larroucau and Rios, 2019; Shorrer and Sóvágó, 2024) showing that applicants deviate from truthtelling by following application strategies is growing. In particular, applicants base their application strategy on admission probability. In experiments participants rank options with a lower payoff but higher chances of assignment above options with a higher payoff but lower chances. In empirical settings, true preferences are harder to identify. For this reason, empirical studies in this literature focus on identifying clearly dominated choices such as ranking a program without financial aid above the same program but with financial aid (Artemov et al., 2020; Hassidim et al., 2021; Shorrer and Sóvágó, 2024). Among the various behavioral explanations for this behavior (Rees-Jones and Shorrer, 2023) , expectation-based loss aversion (Dreyfuss et al., 2022) is a particularly prominent one. By misrepresenting their preferences, applicants lower the reference point for expectations and thus mitigate potential disappointment (Meisner and Von Wangenheim, 2023). Introducing reference dependent preferences in a model of application choices can explain the application behavior observed in experiments (Dreyfuss et al., 2022). We contribute to this literature by providing empirical evidence for strategic application choices based on admission probability. In contrast to other studies, our unique setting allows us to investigate a broader set of application strategies for the full universe of applicants rather than restricting the analysis to one particular clearly dominated strategy.

Second, we contribute to the literature investigating information interventions in centralized admission systems. This literature shows that applicants have biased beliefs on admission probability. Here, a particular focus is on overconfident applicants, who submit truncated applications and thereby risk to remain unmatched (Arteaga et al., 2022; Larroucau et al., 2024). Providing information to applicants in experiments in the field, Arteaga et al. (2022) and Larroucau et al. (2024) show that applicants update their beliefs on admission probability and improve their application choices accordingly. Bobba and Frisancho (2022) model the belief-updating process and show that upward-biased beliefs on students position in the skill distribution can be corrected with applicant-specific information on test performance. We contribute to this literature by showing how applicants react to an applicant-specific, up-to-date but fluctuating information signal on admission probability provided within the application system. In line with the literature, we find that the information can encourage applicants at risk of remaining unmatched to make better application choices. Yet, we also show that the provided information cannot improve all applicants' choices. In the Croatian setting, applicants tend to overreact to the provided information signal, potentially due to misinterpreting it. This emphasizes the importance of how information is provided.

Third, we contribute to the growing literature on dynamic school choice mechanisms, in which applicants interact with the application platform during the assignment process. By that, dynamic systems allow applicants to gather information on their tentative admission outcomes, real-time cutoff scores or their competitors' application choices. The majority of this literature investigates properties of dynamic mechanisms in laboratory experiments (Bó and Hakimov, 2020; Gong and Liang, 2025; Klijn et al., 2019; Stephenson, 2022) or theoretically (Grenet et al., 2022). Most literature finds that dynamic mechanisms enhance truthtelling compared to static systems due to the enhanced information setting of applicants (Bó and Hakimov, 2020), particularly in highly complex choice settings (Gong and Liang, 2025). Empirical literature on dynamic application systems is scarce, potentially due to few applications of dynamic systems worldwide (see L. Chen et al. (2022) for an overview). The empirically-investigated real-world applications of dynamic school choice mechanisms are sequential mechanisms, where applicants apply in groups, starting with the highest scoring applicants. This allows lower-scoring applicants to gain valuable information on admission probability before making their final application choices. In Tunisia, this information enhances truthtelling (Luflade, 2017), but in Inner Mongolia the theoretical benefits of the system (Gong and Liang, 2025) do not translate into practice (Kang et al., 2023). The Croatian dynamic admission system is a novel setting in which applicants make simultaneous choices (rather then sequentially) while learning about their admission probability. Thus, we contribute to the literature on dynamic school choice mechanisms by providing evidence for application strategies in a yet-unstudied dynamic setting.

The remainder of the paper is structured in the following way: In Section 2 we provide a detailed summary of the Croatian application system. In Section 3, we describe the data. In Section 4, we provide descriptive statistics on the dynamics of the Croatian system, which distinguishes it from other application systems. In Section 5 we provide the results of our RDD analysis and in Section 6 we show how applicants develop their application strategy over time while learning about admission probability. Last, in Section 7, we investigate the consequences of following the application strategies we identify in the previous sections. Section 8 concludes.

2 The Repeated DA in Croatia

In Croatia, more than 30,000 high school graduates apply for higher education each year. They choose among more than 700 study programs that are offered by public and private universities and universities of applied sciences throughout the country. Here, a study program is defined as a major in a specific institution. As part of the high school graduation they participate in a centralized school leaving examination, henceforward the state exam, which is held nationwide. All students take three mandatory subject tests in Math, Croatian and a foreign language and can additionally opt for examination in multiple other subjects.

On a central online application platform, applicants rank up to 10 study programs to which they want to apply. Based on applicants' ranking of study programs, their rank-ordered list (ROL), a Deferred Acceptance (DA) mechanism is employed to match applicants to study programs. The DA mechanism matches each applicant to the highest-ranked program for which they can compete with the other applicants. Each applicant is admitted to at most one study program from their ROL or remains unmatched.

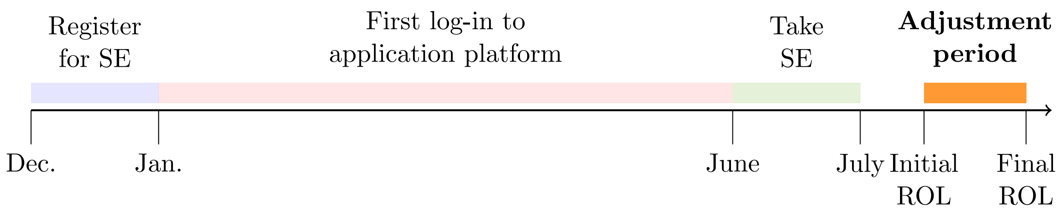
The underlying priority criteria is a score that is composed of weighted high school and state exam grades as well as points awarded for special achievements such as participating in a national competition. Each study program decides autonomously about the weights assigned to the subject grades, the aggregate grades, or the special achievements. This implies that the same applicant can have different admission chances for two programs, even when competing against the same applicants. The last applicant within a programs' quota, i.e., the lowest scoring admitted applicant, determines the minimum score required for admission. Applicants with a score above this cutoff score are admitted, all others are rejected.

The special feature of the Croatian system is that the DA matching process is repeated on an hourly basis. Within a window of about 5-11 days, the application platform publishes information on preliminary matching outcomes. These are the result of running the DA mechanism on the submitted applications (ROLs) of the current hour. Applicants can log in to the application platform to learn their preliminary admission outcome at the current state of applications. Next to observing to which program they are preliminarily admitted, applicants observe the full ranking of applicants and their position therein for each program on their ROL.

Upon receiving this information on the preliminary rankings, applicants can make adjustments to their ROLs. These adjustments can be based on the information they receive, but can also be completely independent thereof. As a consequence of aggregate adjustment behavior, preliminary matching outcomes and the cutoff scores required for admission to each program fluctuate over time.[1] Only at the application deadline do the submitted ROLs become final and cannot be changed anymore. For the last time, the DA mechanism determines a matching based on the final ROLs and applicants are informed of their binding match. This is the study program to which they gain admission.

Hypothetically, applicants must pay the study fees for the program to which they are admitted, regardless of whether they choose to attend or not. However, since this is not enforceable, the only cost of being admitted and not attending is that applicants have to wait for a year to reapply. Applicants who are not admitted can reapply in autumn but compete only for the left-over seats. They can also retake the state exam subject tests, although, if they passed in the first round, only at a cost. Although this option to participate in a second round improves applicants' outside option, admission chances in the second round are lower than in the first as most seats are already taken.

Figure 1: Timeline



The exact timing of the events in the application period is shown in Figure 1. From mid-December to mid-January, applicants register for the state exam subject tests they want to take. As different study programs require passing or assign weight to the grade achieved in a specific state exam subject test, applicants have to be informed about their preferences over study programs already at this early stage. Starting in January, applicants can log into the centralized application platform for the first time. They can already start to construct their ROL and observe preliminary matchings. At this time, the information is not yet conclusive as the matchings are based only on the high school grades of applicants who already registered and constructed their ROL. During the whole month of June, applicants take the state exam subject tests. The grades for all the subject tests are published jointly and the applicants are given a few days to review. After all issues have been resolved, the first informative preliminary matchings are determined and published on the application platform at a time that was publicly communicated. This kicks off the adjustment period, in which applicants receive hourly information updates

[1] Specifically, if an applicant with a score higher than the cutoff score decides to add a program to the top of their ROL, she drives out the previously last admitted applicant. The previously second to last admitted applicant now moves to the lowest rank within the quota and determines the new cutoff score. The cutoff score increases. Meanwhile, if an applicant with a score below the cutoff score applies to the program, the cutoff score remains unchanged. Additionally, the cutoff score of another program is affected by the one applicant's decision as well. The applicant who was driven out of the quota now applies to his next-ranked program and potentially drives out the last admitted applicant to this program himself. In this way, cutoff score fluctuations are passed on from one program to the next, even if only one applicant decided to adjust their ROL.

on preliminary matches. For our research, we focus on the adjustment period, starting with the initial ROL, which are the preference rankings submitted just before the first preliminary matchings are published. The exact timing of events differs between cohorts, but all dates are publicly communicated. We provide an overview of the exact event timing in the Appendix (Panel a) of Table A1).

3 Data

The data used in this project is administrative data from the centralized admission system in Croatia provided by the Agency for Science and Higher Education. For the whole universe of applicants in the cohorts 2012 - 2015, we observe hourly application choices (ROLs) and the corresponding preliminary admission outcomes. This includes information on the program to which each applicant is temporarily admitted, as well as each applicant's rank position in the programs' ranking of applicants. In addition, we observe the scores with which applicants apply to each program if an applicant ever adds the program to their ROL. At the program level, we observe the number of seats or quota offered by each program. On the applicant level, we observe all high school subject grades, state exam subject grades, and their gender. By combining quotas, program's rankings of applicants, and applicants' scores, we compute a cut-off score for each program in every hour within the adjustment period. Based on this, we compute for each applicant the distance to the cut-off in terms of points and rank positions.

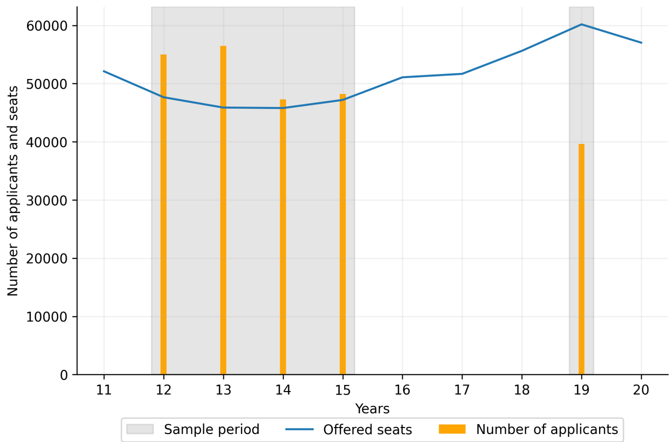
In 2019, we conducted a survey on the universe of applicants. Before registering on the application platform, the applicants responded to our survey in order to proceed with the log-in. The questions in the survey appeared one by one. Applicants were asked: 1) *"Imagine a situation where you can enroll in any study program in Croatia, regardless of the points you have achieved. Which study program would you choose?"* 2) *"In case you give up your first choice, which study program would be your second choice?"* 3) *"In case you give up your second choice, which study program would be your third choice?"*. After they locked their top-3 preferences we asked to elicit their beliefs on admission probability to each program listed previously. Applicants could not revise their answer to the previously answered questions after observing the next question.

For our analysis in Section 6.2, we combine our survey data with administrative data similar to the data described for the earlier cohorts above. As in 2019 we do not observe hourly ROLs directly, we use data on real-time changes made by applicants to their ROLs to recreate applicants hourly ROLs.

Overall, we have information on about 35,000 applicants applying to more than 700 programs over an adjustment period that lasts 5-11 days, depending on the cohort. On average, applicants rank about 4 programs on their ROL per hour. This results in 8.8 - 20.7 million observations per cohort. The exact numbers for each cohort are shown in Table 1.

In Figure 2 we show the number of applicants relative to the number of seats offered by universities per cohort. Although in 2012 and 2013 demand for seats exceeds supply, demand can be largely met in 2014 and 2015. Only in 2019 more seats are offered than applicants apply for. This implies that the competition for programs changes over time. In a nutshell the real measure of demand is the number of applicants times the number

Figure 2: Number of applicants and seats by cohort



Note: Figure shows the number of applicants applying via the centralized application system and the number of seats offered by universities per cohort. The shaded areas highlight the years in our sample.

of choices, which is always far greater than number of available seats. From year to year the demand for programs is not necessarily equally distributed, we show in Panel b) of Table A1 in the Appendix the number of overdemanded programs and the magnitude of overdemand per cohort.

Table 1: Summary statistics

	2012	2013	2014	2015
# programs	727	759	767	780
# overdemanded programs	313	296	251	358
# applicants	34,735	34,922	35,938	36,759
# hours	83	118	216	98
avg. length ROL	4.07	3.87	3.57	4.58
# observations	8,790,011	12,053,877	20,669,729	13,378,643

Note: Table shows the total number of study programs, the number of study programs with overdemand, the number of applicants, the number of hours, the average number of ranked programs and the total number of observations in each sample (2012, 2013, 2014 and 2015).

4 Dynamics of the Repeated DA

The main feature that distinguishes the Croatian system from other applications of the DA is its iterative character. While in other systems, applicants construct their preference ranking without any individual-specific information, applicants in Croatia receive hourly information signals on their preliminary matching outcome under the current status of application. We consider the preliminary match result an information signal on applicant- and program-specific admission probability. From preliminary matchings, but also from applicants' distance to the cut-off, i.e., by how close they did or did not make it, they can deduct a proxy for applicant-specific admission probability.

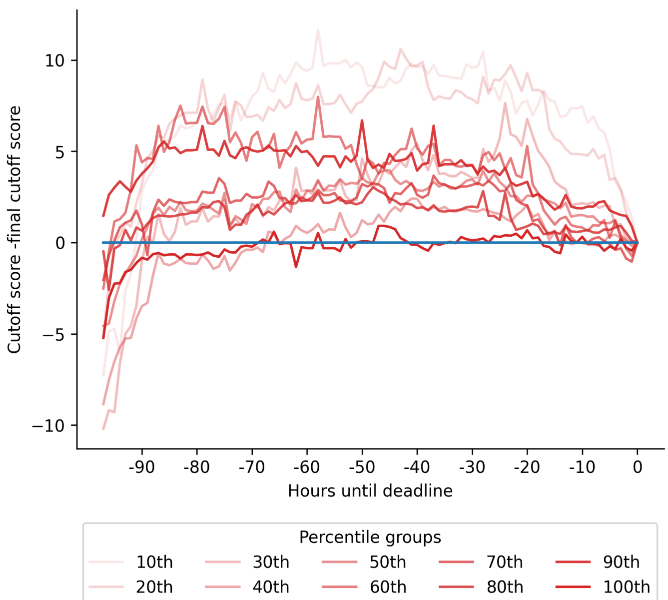
Based on updated beliefs about admission probability, applicants can continue searching for programs to add to their ROL. For example, an applicant who observes a low admission probability to all programs in their ROL might want to add a program with a higher admission probability. Another applicant with a high admission probability to most of their ranked programs might want to look for a more ambitious program. Additionally, since application choices are not final until the application deadline, applicants can experiment with their choices over the course of the adjustment period. Only by adding a program to their ROL they can receive a signal and learn about admission probability.

As a consequence of applicants adjusting their ROLs to the new information, the Croatian system develops its own dynamic. With new applicants entering the competition for programs, the cutoff scores fluctuate. Thus, even an applicant who does not make any changes to their application choices from one hour to the next may observe a change in information signals about admission probability. First, this implies that the information signal should be regarded as a fuzzy signal rather than a fully informative one on the final admission probability. Second, fluctuating cut-off scores add further uncertainty, which might influence applicants' choices. In this first part of our research, we investigate the dynamic implications of the repeated DA.

4.1 Volatility in Program Cutoffs

Unlike in a static DA, where there is only one program-specific cut-off for a cohort, applicants in a repeated DA setting observe hourly fluctuating admission cut-offs for every program. On one hand, this imposes additional informational uncertainty for programs with high cutoff score volatility. On the other hand, this system allows applicants to explore other options outside their initial set of preferences and to learn about admission chances.

Figure 3: Cutoff score fluctuations over time (relative to the final cutoff)

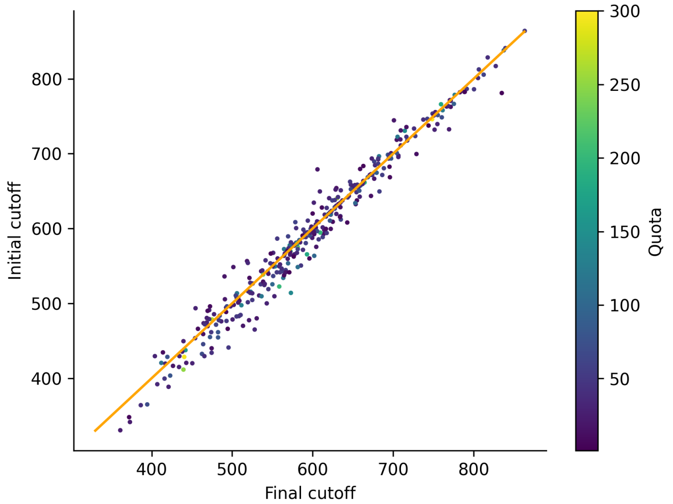


Note: Figure shows cutoff score fluctuations over the adjustment period. The y-axis shows the difference between the current and the final cutoff score. A positive value means that the current cutoff score is higher than the final cutoff score. We aggregate the deviations from the final cutoff score of 10 percentile groups of programs based on the final cutoff score. The 100th percentile group are the 10% of programs with the highest final cutoff score, i.e., the most competitive programs.

In Figure 3 we show for 2015 how the cutoff score evolves over time. We group programs into 10 groups according to their absolute cutoff score. Programs in the highest percentile group are the most competitive programs with the highest final cut-off score. The y-axis shows the group average of the relative cutoff score, i.e., the hourly cutoff score deviation from the final cutoff score. The x-axis shows the time left until the application deadline, when the application choices are final. Apart from the very first hours, the hourly cutoff score lies above the final cutoff, implying higher preliminary admission criteria than the relevant final one. On average, the hourly cutoff score for each group never deviates by more than 10 points from the final cutoff. However, the magnitude of cutoff score deviations differs by percentile groups, with the least competitive programs showing larger average deviations from the final cutoff score. This pattern is even clearer in the cohort 2012 - 2014 as shown in Figure A1 in the Appendix.

Similarly, Figure 4 shows the change in the cutoff score from the beginning of the adjustment period (initial ROL) to the application deadline for single programs. Each program is represented by a marker. Markers below the 45-degree line are programs whose final cut-off score lies below the initial cutoff score. Across the full distribution of programs by final cutoff score, there are programs which experience an increase and a decrease in cutoff scores over time. However, larger changes in the cutoff score seem more common for programs with lower to medium final cutoff scores. At the upper end, markers are distributed closer around the 45-degree line. Although we observe this pattern by competitiveness, cutoff score changes seem not to be correlated to the programs quota. The figure looks similar for the other cohorts (Figure A2). Panel c) of Table A1 in the Appendix shows the absolute number of programs with an increasing, decreasing, or constant cutoff score between the initial and final ranking. In all cohorts, but 2015, the number of programs with a decreasing cutoff score is 2-3 times higher than the number of programs with an increasing cutoff score. Only in 2015 the number of programs with an increasing and decreasing cutoff score are comparable.

Figure 4: Initial and final cutoff scores



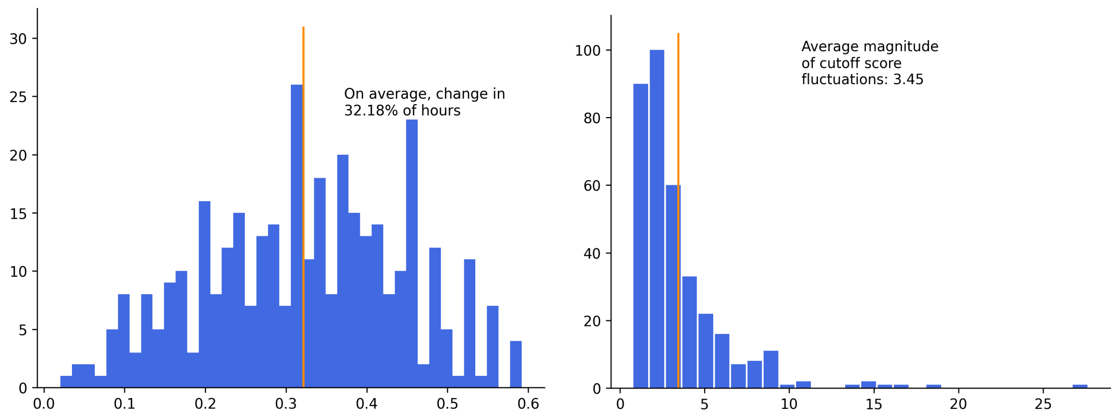
Note: Figure shows for each program the initial cutoff score at the beginning of the adjustment period and the final cutoff score. Each program is represented by one marker, colored by the program's quota size. Programs above the 45-degree line are programs whose cutoff score decreases over time, programs below the 45-degree line are programs whose cutoff score increases over time.

Next, we investigate whether programs differ in their number of cutoff score fluctuations. Panel a) of Figure 5 shows the share of hours in which the cutoff score of a program changes relative to the previous hour in 2015. Although some programs cutoffs change in almost 60% of hours, other programs cutoff scores remain largely constant over time. The cutoff score of the average program changes in 32.18% of hours. In the previous cohorts the number of changes are slightly lower but comparable (see Figure A3).

Figure 5: Distribution of programs by number and avg. magnitude of fluctuations

(a) Share of hours with fluctuations

(b) Avg. magnitude of fluctuations



Note: Panel a) shows the distribution of programs by the share of hours in which their cutoff score changes. For Panel b) we aggregate the the (absolute) cutoff score fluctuations of each program over the adjustment period conditional on the cutoff score fluctuating. We show the distribution of programs by their average absolute magnitude of cutoff score fluctuation.

Additionally, programs differ in the magnitude of fluctuations.[2] Panel b) of Figure 5 shows that, conditional on the cutoff score changing, the average cutoff score fluctuates by 3.45 points. Some programs have average cutoff score fluctuations of only one point while few programs experience average cutoff score fluctuations by more than 10 points. Figure A4 in the Appendix shows the results for the other cohorts.

Last, we investigate whether the number and magnitude of fluctuations are correlated with program characteristics, i.e., quota and competitiveness. Panel a) of Figure 6 shows that larger programs experience more cutoff score fluctuations while, conditional on the quota, the cutoff score of more competitive programs fluctuates less frequently. Panel b) of Figure 6 shows that larger programs experience fluctuations of lower magnitude. Thus, although the cutoff score of programs with a higher quota fluctuates more frequently, the fluctuations are of lower magnitude. As cutoff score fluctuations are driven by changes in the set of applicants above the cutoff, larger programs are more likely to experience a change. Figures A5 and A6 show the results for the other cohorts.

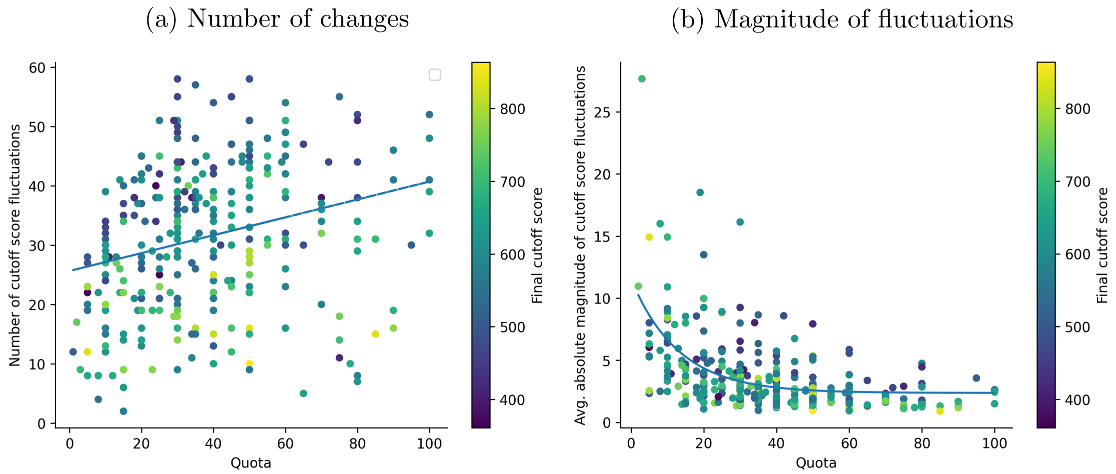
4.2 Adjustment behavior and updating beliefs on admission probability

While changes in the cutoff scores induce applicants to adjust their choices, it is the aggregate adjustments that drive the cutoff score fluctuations. Thus, adjustments induce further adjustments.

In Figure 7 we show the share of applicants who make at least one change to their ROL in an hour of the adjustment period for all 4 cohorts of 2012 - 2015. The dashed vertical lines show the start and end date of the adjustment period per cohort, which differ slightly across the years. Yet, the cohorts exhibit similar behavioral patterns. First, the share of applicants who make at least one change is particularly high in the very beginning

[2]As cutoff score fluctuations are often partly reversed in a following hour, we use the absolute change to compute the average as otherwise positive and negative fluctuations cancel each other out.

Figure 6: Number and magnitude of fluctuations by program characteristics

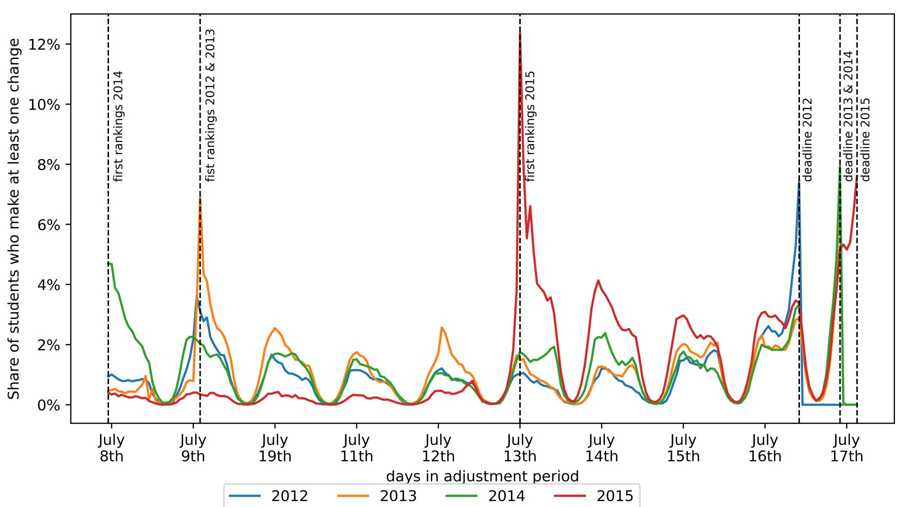


Note: Panel a) shows programs by their number of cutoff score fluctuations and quota. Each marker represents a program colored by their final cutoff score. Programs with a higher quota experience more cutoff score fluctuations and conditional on the quota, programs with a higher cutoff score also experience fewer fluctuations. Panel b) shows programs by their average absolute magnitude of cutoff score fluctuations, conditional on the cutoff score fluctuating and by their quota. Programs with a higher quota experience fluctuations of smaller magnitude.

of the adjustment period. Depending on the cohort, 5 - 12% of applicants adjust their ROL in the very first hour of the adjustment period. A potential explanation for this is that at this time, applicants receive the very first signal on admission probability. As prior beliefs are only subject to applicants' subjective assessment of admission probability, the first information signal likely induces the strongest belief-updating and consequently the strongest reaction.

The following fluctuations reflect day-night cycles, where up to 4% of applicants adjust their ROL in a single hour during the day and hardly anyone adjusts their ROL at night.

Figure 7: Share of applicants who adjust their ROL



Note: Figure shows the share of applicants making at least one change to their ROL in each hour of the adjustment period for the cohorts 2012-2015. The vertical dashed lines mark the beginning and the end of the adjustment period.

In the last hour of the adjustment period, the share of applicants who adjust their

ROL increases again. About 6% of the applicants adjust their ROL just before the application deadline. But also in the hours leading up to the application deadline, the share of changing applicants is higher. As applicants approach the application deadline, the information signal becomes clearer and more relevant. An increasing number of applicants approach their final choices as they experimented with all programs they consider relevant and evaluated their choices in the previous hours. This can also be seen in Figure 3, which shows that the cutoff scores converge to their final value over the last few hours of the adjustment period. In addition, applicants approach their final choices and might take the information signals more seriously.

Although this is only suggestive evidence and we hypothesize about explanations for observed behavior, we provide causal evidence for applicants' reaction to signals on admission probability in the next chapter.

5 Reaction to signals on admission probability

In the second part of our paper, we investigate whether applicants consider the probability of admission in their application choices. Via the application platform, applicants to higher education in Croatia receive hourly information signals on admission probability. Although applicants can derive admission probability from their distance to the cut-off in terms of points or rank positions, the strongest signal they receive is the information on whether they are, at the current state of applications, above or below the cut-off. We take advantage of the sharp (preliminary) admission cutoff that sorts applicants into groups that receive either a positive or negative preliminary admission signal.

Applicants above and below the cutoff point are arguably very similar. First, they are highly comparable in their grades as reflected in the score based on which applicants are admitted. Second, they chose to apply to the same study program. Third, due to fluctuating cutoff scores, applicants in a narrow bandwidth around the cutoff are exogenously distributed to receive a positive and negative preliminary admission signal. As cutoff score fluctuations are driven by other applicants' choices, a single applicant cannot influence the signal she receives. Lastly, applicants who are above the cutoff in one hour might be below the cutoff in the next. Thus, to some extent, applicants above and below the cut-off are not only highly comparable but are actually the same.

5.1 Methodology

We estimate the following econometric specification:

$$\text{Change}_{i,t,p} = \beta_0 + \beta_1 \text{Above}_{i,t,p} + \beta_2 \text{Dist}_{i,t,p} + \alpha_p + \epsilon_{i,t,p} \tag{1}$$

where $\text{Change}_{i,t,p}$ equals 1 if applicant i at time t makes any change to the study program p that is currently on the first rank position of their ROL. $\text{Above}_{i,t,p}$ is a dummy that indicates whether an applicant has a score above the admission cut-off and therefore receives a positive preliminary admission signal. $\text{Dist}_{i,t,p}$ is our running variable and indicates an applicant i's rank position relative to the cutoff score or quota of program p. α_p are program-fixed effects.

We estimate this model for the programs on the first three preference ranks, because on average more than 85% of individuals are admitted to one of their three highest ranked programs. In Section 4.1 we provide evidence for systematic differences in the frequency and magnitude of cutoff score fluctuations between programs that are related to program characteristics. This allows risk-averse applicants to select programs with fewer or smaller cutoff score fluctuations. We account for this possibility of selection with program FE.

Due to data restrictions, we do not observe whether an applicant logs in to the application platform and observes the signal on admission probability. To partly account for this, we further restrict the sample of the RDD regression to the last 10 hours before the application deadline. Towards the end of the adjustment period the share of applicants who make at least one change increases, which increases the probability that they logged in to the application platform and actually observed the signal. Yet, this does not fully solve our data limitation, which is why our results can be regarded as lower bounds.

5.1.1 Choice of bandwidth

To ensure that applicants above and below the admission cut-off are highly similar, particularly in terms of the information signal they receive, we define the bandwidth on the program level based on the quota. For each program, we select the 10, 20 or 30% of lowest performing applicants within the quota and the same number of highest scoring applicants just below the quota. This measure of relative rank position is closely related to admission probability and accounts for differences in quota, and density around the cutoff point. Programs with a larger quota receive a stronger weight in the regression, which reflects the number of applicants who apply to these programs.

The intuition is the following. Applicants react to the information signal on admission probability they receive (negative when below the cut-off point). An applicant who is 10 rank positions below the cutoff of a program with a quota of 100, would perceive the negative signal as weak, since still being very close to the cutoff (top 10% of applicants below the cutoff). In contrast, a ranking of 10 below the cutoff point of a program with a quota of 20 might be perceived as a stronger negative signal. By restricting the sample by relative rank position, we select only applicants who receive a similar signal on admission probability and exclude applicants who receive a very strong positive or negative signal and have a significantly higher or lower admission probability than students just around the cutoff in relative terms.

In Table 2 we show exemplary for 2015 how the information signal differs for applicants within the bandwidth. Here, the full sample is only restricted by the bandwidth of 10, 20 or 30% of the quota around the cutoff. The RDD sample is additionally restricted to applicants' highest-ranked program and contains only the last 10 hours before the application deadline. As the bandwidth increases, the maximum point difference in terms of distance to the cutoff increases from about 16 to 34 and to 51 for a bandwidth of 30%. Importantly, the average admission probability for applicants above and below the cut-off is highly similar in all the samples. Table A2 shows the summary statistics for all cohorts.

5.2 Results

First, we show that applicants react to the information signals in a reduced form analysis. We use three different information treatments, which all signal admission probability. Moving up by one point relative to the cutoff score increases admission probability by

Table 2: Summary statistics RDD sample, 2015

	10% (1)	20% (2)	30% (3)	10% RDD (4)	20% RDD (5)	30% RDD (6)
Min. point distance	-12.49	-24.13	-34.18	-6.71	-16.53	-25.16
Max. point distance	15.89	26.28	35.67	9.54	18.25	26.50
Min. rank distance	-5.08	-10.48	-15.60	-4.90	-10.13	-15.01
Max. rank distance	5.08	10.49	15.67	5.00	10.32	15.47
Avg. adm.prob. below	0.96	0.94	0.93	0.97	0.95	0.93
Avg. adm.prob. above	0.97	0.98	0.98	0.98	0.98	0.98

Note: In this table we show the range of scores, rank positions and admission probability in each of six samples. To compute the minimum point distance we take for each program the lowest score within the sample and subtract the cutoff. For example, the average minimum point distance in Column 1 of -12.49 means that across all programs the lowest scoring applicant within the sample scores on average 12.49 points below the cutoff score. Similarly, applicants within the sample of Column (1) are up to 5.08 ranks below and up to 5.08 ranks above the cutoff/quota. The average admission probability below the cutoff is 96%, that of applicants above the cutoff is 97%. The samples in Columns (1)-(3) are restricted only by the relative rank distance i.e., 10, 20 or 30% of the quota. The samples in Columns (4)-(6) are additionally restricted to the last 10 hours of the adjustment period and to applicants' highest ranked programs. These are the samples we use for all RDD regressions.

Table 3: Information signals and Probability to change, 2015

	Dep. var.: 1[Change] $\times$ 100		
	Point distance	Rank distance	Above/Below
(1)	(2)	(3)	
Distance	-0.0034***	-0.0023***	-0.6461***
	(0.0002)	(0.0001)	(0.0295)
Constant	4.2840***	4.2571***	4.6148***
	(0.0148)	(0.0149)	(0.0204)
Program FE	No	No	No
Observations	1,900,603	1,900,603	1,900,604
R-squared	0.0002	0.0002	0.0002

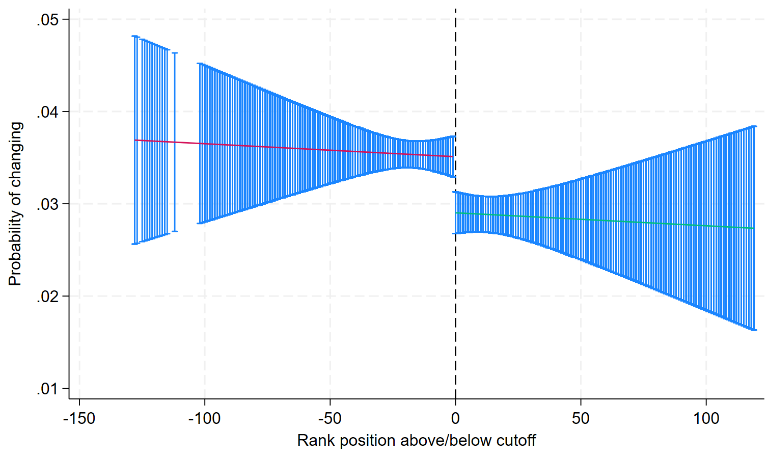
Note: Table shows the coefficients of regressing three different types of information signals on a dichotomous variable that equals 1 if an applicant changes a program at time t. The information signal in Column 1 is the distance to the cutoff in terms of points. Below the cutoff, the distance is negative, above the cutoff it is positive. The coefficient of -0.00003 means that as applicants below the cutoff move closer to the cutoff and applicants above the cutoff move further away by one point, the probability to change declines by 0.003 pp. Similarly, the information signal in Column 2 is the rank distance to the cutoff. In Column 3 the information signal is dichotomous and equal to 1 if an applicant is above the cutoff and zero otherwise. Applicants above the cutoff are 0.65pp less likely to adjust their ROL. Robust standard errors in parentheses. * p-value $<$ .1, ** p-value $<$ .05, *** p-value $<$ .01.

bringing applicants below the cutoff closer to it and increasing the distance to the cutoff for applicants above the cutoff. The same is true for moving up by one rank position. Applicants below the cutoff reduce the rank distance while applicants above the cutoff increase the rank distance to the cutoff. For both, this implies an increase in (perceived) admission probability. As a third information signal we use the dichotomous signal of being positioned above or below the cutoff, which is arguably the signal perceived most strongly by the applicants.

The reduced form results are shown in Table 3. Tables A3, A4 and A5 in the Appendix show results for the other cohorts. Moving up by one point reduces the hourly probability of changing the program at the first position of an applicant by 0.0013 to 0.0034 pp in all cohorts. Applicants who experience the average cutoff score fluctuation of 3.5 points are 0.005 - 0.012 pp less likely to change. The results look similar for rank positions, shown in Column (2). In line with the dichotomous signal being perceived most strongly, Column (3) shows the largest coefficients: applicants above the cutoff are 0.25 - 0.65 pp less likely to adjust their first preference than applicants below the cutoff. Relative to the baseline probability to change, students above the cutoff have a 5.2 - 14.1% lower probability to change.

When analyzing the magnitude of the coefficients we have to consider that applicants do not always observe the hourly information signals as they have to log in to the application platform to do so. Yet, we treat applicants as receiving the signal on an hourly basis as we do not observe their log-in behavior. This puts a strong downward pressure on our estimated results. For the reduced form analysis in Table 3 we use all hourly observations during the adjustment period. To circumvent this issue in our main analysis, we reduce the sample to only the last 10 hours of the adjustment period for two reasons. First, as can be seen in Figure 7 the share of applicants who make a change increases significantly in the last hours, which indicates that many applicants log-in to the application platform. Second, as only the last submitted ROL is relevant for the final admission outcome, more applicants might be inclined to log-in in order to receive the more relevant information. Thus, reducing the time observations in our sample should reduce the concern of underestimation although it cannot be eliminated.

Figure 8: Probability to change around the admission cutoff, 2015



Note: Figure shows the discontinuity in the probability to change the program on the first rank when receiving a positive and negative preliminary admission signal. It is the result of Equation 1 for the sample from 2015 and a bandwidth of 20% of the quota above and below the cutoff. The vertical lines show the 95% confidence interval.

Exploiting the RDD setting outlined above, we show that applicants' strategic behavior is driven by changing beliefs on admission probability. Exemplary, Figure 8 depicts a clear discontinuity in the probability to adjust the ROL at the cutoff in 2015 for a bandwidth of 20% of the quota around the cutoff. Column (1) of Table 4 shows that applicants who receive a positive preliminary admission signal are 0.6 pp less likely to adjust their ROL than applicants below the cutoff who receive a negative preliminary admission signal. Relative to the baseline probability to change of 3.5%, this is an increase by more than 17%. This can be interpreted as applicants reacting to the negative information signal by downward-adjusting their beliefs on admission probability. They omit study programs from their ROL for which admission seems less likely. Our results thus show that appli-

Table 4: Distance to cutoff and Probability to change, bandwidth = 0.2, 2015

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.592***	-0.608***	-0.815**	-0.794*	-1.587***	-1.773**
	(0.211)	(0.227)	(0.409)	(0.440)	(0.603)	(0.736)
Distance	-0.001	-0.001	0.036***	0.036***	0.028**	0.020
	(0.005)	(0.005)	(0.007)	(0.009)	(0.012)	(0.015)
Constant	3.506		5.268		5.711	
Program FE	No	Yes	No	Yes	No	Yes
Observations	48,678	48,678	19,511	19,511	10,145	10,145
# Programs		351		325		284
R-squared	0.0003	0.0003	0.0010	0.0006	0.0007	0.0006

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

cants incorporate perceived admission probability into their application choices and act strategically. We repeat the analysis for bandwidths of 10% and 30% of each programs' quota around the cutoff and for cohorts 2012 - 2014 (Tables A6, A7, A8, A9, A10, A11, A12, A13, A14, A15, A16 in the Appendix). Across all years and bandwidths, applicants above the cutoff are between 0.4 and 1 pp more likely to change (conditional on the coefficients being statistically significant), which corresponds to an increase of 11 - 23% relative to the baseline probability to change.

We repeat this analysis for programs on ranks 2 and 3. Here, we condition the sample on applicants who are not admitted to any of their higher ranked programs. Only for 2015 we find significant evidence for a reaction to a negative preliminary admission signal. Applicants above the cutoff are 0.6 - 3 pp less likely to adjust their second or third preferences. Relative to the baseline this is an increase by 12 - 46.9%. Yet, due to lacking evidence for cohorts 2012-2014, we cannot conclude that applicants react to the information signal of the second- and third-ranked program.[3]

5.3 Robustness checks and Heterogeneity

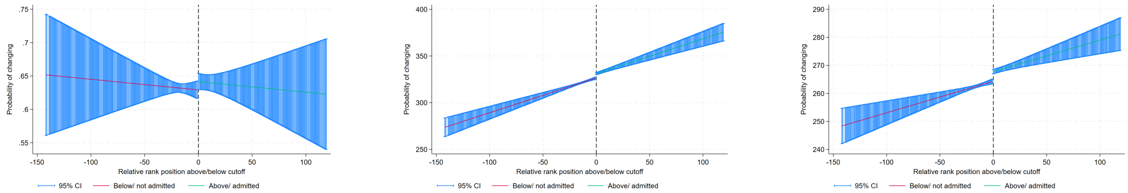
To further support our results we conduct multiple robustness checks and heterogeneity analyses. First, we show in Figure A15 that there is no discontinuity in confounding factors i.e., the share of women and weighted high school and state exam points at the cutoff.[4]

[3]This lack of a statistically significant reaction might also be driven by applicants reacting to the negative information signal they receive for a higher ranked program. As for this exercise we condition the sample on applicants who are below the cutoff of any higher ranked program, they might also react to this negative signal by making a change to their lower ranked, i.e., second- or third-ranked, program. We would observe this as an adjustment as a reaction to the either positive or negative signal for the second- or third-ranked program, which might blur our results.

[4]The small jump in weighted state exam and high school grades are of small magnitude (about 2 points) compared to the average state exam/ high school grade of about 325/265. Thus, we argue that this minor discontinuity is negligible and applicants just above and below the cutoff are comparable in terms of ability.

Figure 9: No discontinuity in counterfactuals, bw = 20%, 2015

(a) Share female (b) Weighted State Exam Grades (c) Weighted High School Grades



Note: Figures are based on Equation 1 using as dependent variable a gender dummy (Panel a)), applicants' weighted state exam grades (Panel b)) and weighted high school grades (Panel c)). The sample is the 2015 cohort under bandwidth restrictions of 20% of the quota above and below the cutoff. The vertical lines show the 95% confidence interval.

Table 5: Distance to cutoff and Probability to change, bandwidth = 0.2, 2015

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.205	-0.267	-0.426***	-0.443***	-0.003	-0.003
	(0.188)	(0.202)	(0.138)	(0.137)	(0.003)	(0.003)
Distance	0.002	0.004	0.005*	0.005*	0.001***	0.001***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.000)	(0.000)
Constant	2.634		2.883		.1	
Program FE	No	Yes	No	Yes	No	Yes
Observations	48,678	48,678	98,090	98,090	52,088	52,088
# Programs		351		354	351	351
R-squared	0.000026	0.000034	0.000093	0.000089	0.001651	0.001651

5.3.1 Types of changes

Second, we further specify the reaction to the information signal by investigating whether it affects the probability of applicants to drop the program from their ROL completely. Previously, we restricted our analysis to the highest ranked program as only here the direction of change is clear: applicants can only move it to a lower rank or delete it from their ROL. Now, we can investigate applicants reaction to information signals on all programs as the direction of change is clear when applicants delete a program. The results for 2015 are shown in Columns (1)-(4) of Table 5 and for other years and other bandwidths in Tables A17, A18, A19, A20, A21, A22, A23, A24, A25, A26, A27.

Overall, we find some evidence for applicants being more likely to delete a program on any rank when receiving a negative preliminary admission signal. In all cohorts we find a largely negative correlation between -0.1 - 0.4 pp. In 2012, 2013 and 2015, this correlation is largely statistically significant, depending on the bandwidth. Relative to the baseline probability to delete a program, applicants are between 8.6 and 14.7% less likely to delete a program when they are above the cutoff.

For the highest ranked program we find statistically significant evidence only for 2013. In 2013, applicants above the cutoff are 0.6 - 0.7 pp less likely to delete the affected program, which corresponds to an increase of 17.6 - 18.7% relative to the baseline probability to change a program of 3.6%. Although we find a negative correlation also for the cohorts 2012 and 2015, the coefficients remain statistically insignificant.

Third, we investigate the impact of the information signal on the probability to

Table 6: Distance to cutoff and Probability to change, bandwidth = 0.2, 2015

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.690**	-0.755**	-0.430	-0.377	-0.430	-0.388
	(0.269)	(0.314)	(0.338)	(0.316)	(0.338)	(0.298)
Distance	-0.001	-0.004	0.000	0.000	0.000	-0.001
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Female					0.214	0.345
					(0.281)	(0.278)
Above × Female					-0.260	-0.361
					(0.432)	(0.419)
Female × Dist					-0.002	-0.001
					(0.009)	(0.008)
Constant	3.581		3.367		3.367	
Program FE	No	Yes	No	Yes	No	Yes
Observations	29,925	29,925	18,753	18,753	48,678	48,678
# Programs		330		302		351
R-squared	0.0004	0.0004	0.0001	0.0001	0.0003	0.0003

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

extend the ROL. This particular behavioral response is interesting as it increases applicants probability to be matched to any program. The information signal might encourage applicants at risk of not being matched at all who initially rank fewer than the allowed 10 programs to extend their ROL. Columns (5)-(6) of Table 5 shows the results. For none of the cohorts we find significant effects. The information signal on admission probability for the highest ranked programs seems to not induce applicants to extend their ROL.

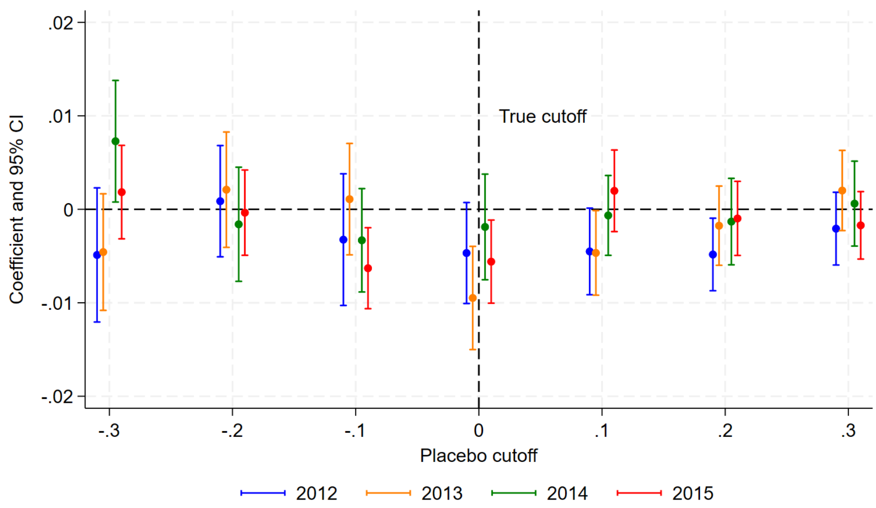
5.3.2 Heterogeneity by gender

To investigate whether the results are driven by only one gender, we distinguish male and female applicants a) by running separate regressions for a male and female sample and b) by interactions. Table 6 shows the results for 2015. For this cohort, only women seem to react to the information signal on admission probability. Female applicants who receive a positive preliminary admission signal are 0.76 pp less likely to adjust their preferences than female applicants below the cutoff. Relative to women's baseline probability to change of 3.6% this is an increase in by 21.1%. Meanwhile, we do not observe a significant reaction to the information signal by men. Yet, these results are not consistent across the cohorts (see Tables A28, A29, A30, A31, A32, A33, A34, A35, A36, A37, A38,). For 2012 and 2013, we find significant coefficients of similar size for both men and women. For 2014 we do not find any significant coefficients. Thus, we cannot conclude that there are clear gender differences in the reaction to the information signals, although we find more consistent evidence for women.

5.3.3 Placebo test

For further robustness we repeat the RDD estimation using placebo cutoff scores. We identify placebo cutoffs as the score of the last admitted applicant under a quota that is 10, 20 or 30% higher or lower than the actual quota. For example, to obtain the estimate for a cutoff score under a quota reduced by 10%, the placebo cutoff for a program with a quota of 100 is the score of the 90th admitted applicant.

Figure 10: Coefficients with placebo cutoffs



Note: Figure shows the coefficients and 95% confidence bands of Equation 1 using placebo cutoffs. For example, for the placebo cutoff at -0.1 we push the cutoff down by 10% of the quota. For a program with a quota of 100, this implies that the cutoff is at the score of the applicant on rank 10 below the actual cutoff. Similarly, we push the cutoff up for regressions with positive placebo cutoffs, right to the vertical dashed line. We show results for all four cohorts.

In Figure 10 we show the coefficients and 95% confidence bands for estimations with cutoff scores under 10, 20 and 30% increased and reduced quotas. Although we find statistically significant estimates also at a cutoff score moved up or down by 10% of the quota, the results look best for the true cutoff score. A potential explanation for significant coefficients with the closest placebo cutoff is that applicants not only react to the dichotomous signal but also to the point distance. As the point distance to the placebo cutoff and of the true cutoff are correlated, this might drive the significant results for placebo cutoffs.

6 Developing a strategy

In chapter 5.2 we established that applicants react to signals on admission probability, which implies that beliefs on admission probability feed into application choices. Applicants who receive a negative preliminary admission signal are more likely to change or delete the affected program and more likely to extend their ROL. So far, we only looked at single decisions that are driven by the information provided by the repeated DA system. Only jointly these decisions compose a strategy and only at the end of the adjustment period applicants' strategy is binding. Before then, applicants can play with their choices to gather information on the probability of admission and to develop their final strategy. In this chapter, we investigate how applicants develop their final application strategy over time.

6.1 Risk to remain unmatched

The most consequential application error is to compose a ROL with a high risk of not being matched to any ranked option. Due to overestimating admission probability to the ranked programs, applicants who rank low-probability programs only and/or (additionally) submit a shorter than allowed ROL, might end up unmatched although feasible programs that they prefer over their outside option are available. As applicants in the Croatian system receive signals on admission probability and observe if they are unlikely to be matched to any ranked program, the repeated DA mechanism might help to diminish this risk.

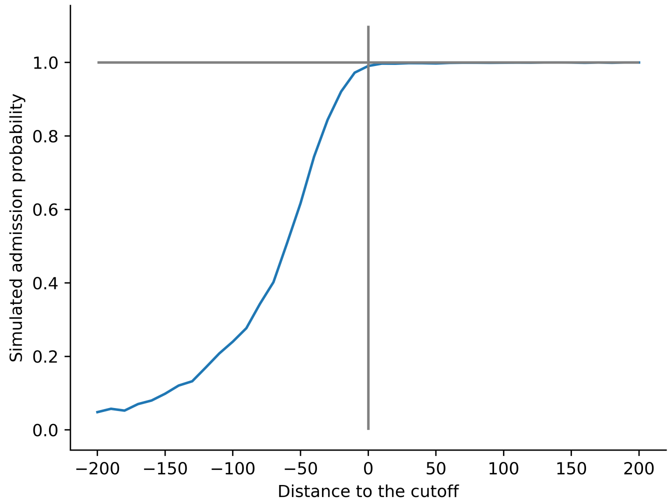
To investigate how the risk of remaining unmatched evolves over the adjustment period, we compute for each applicant × program combination a measure of admission probability. Drawing from the set of observed final ROLs with multiple-drawing, we create 500 artificial samples, each containing the number of applicants who apply to at least one program at the application deadline. By restricting the set of ROLs from which we draw to contain only those submitted in the last hour before the application deadline, we ensure that our results are not driven by time trends in application choices. Each sample reflects the final application choices based on which the binding matchings are computed. We replicate the DA mechanism as it is implemented in Croatia and rerun it for each of the 500 artificial samples. From this we obtain matching results for each of the 500 samples and can compute the admission cut-off for each program. In this way, we obtain a distribution of possible cut-off scores for each program and can determine the share of scenarios in which each applicant has a score higher than the cutoff score. This share reflects the probability of admission of an applicant for a specific program. The computed admission probability does not vary over time and is therefore independent of cutoff score trends. However, the probability of remaining unmatched can change over time as a result of applicants changing the composition of their ROL.

Figure 11 shows for 2015 how our simulated admission probability evolves around the admission cutoff. Admission probability increases as applicants approach the admission cutoff and increasingly so, following an S-curve. Applicants up to 25 points below the cutoff have an admission probability of about 90%. In 2012 and 2014 this looks slightly different, with applicants at the cut-off having an admission probability of only about 80%. The results for 2013 are somewhere between; here applicants at the cut-off have an admission probability of about 90%. The results for all years are shown in Figure A20 in the Appendix.

Using the simulated admission probabilities, we computed for each of applicants' ROLs the risk to remain unmatched as the product of each ranked program's specific risk of being rejected.

We show in Panel a) of Figure 12 how the risk to remain unmatched evolves during the adjustment period. Here, the x-axis denotes the time left to make adjustments in hours until the application deadline, when the time left is zero. The aggregate risk to remain unmatched declines by about 3 pp from an initial risk of 11% to a risk of 8% at the application deadline. This aggregate trend covers a significantly sharper decline for the most-at-risk applicants as can be seen in the subgroup analysis in Panels b) - d) of Figure 12. While the large majority of applicants' risk does not change significantly, applicants with an initial risk of 90-100% (Panel d)) experience a strong decline of approximately 20

Figure 11: Simulated admission probability around the admission cutoff, 2015



Note: Figure shows how the simulated admission probability evolves around the admission cutoff. The vertical line shows the final cutoff.

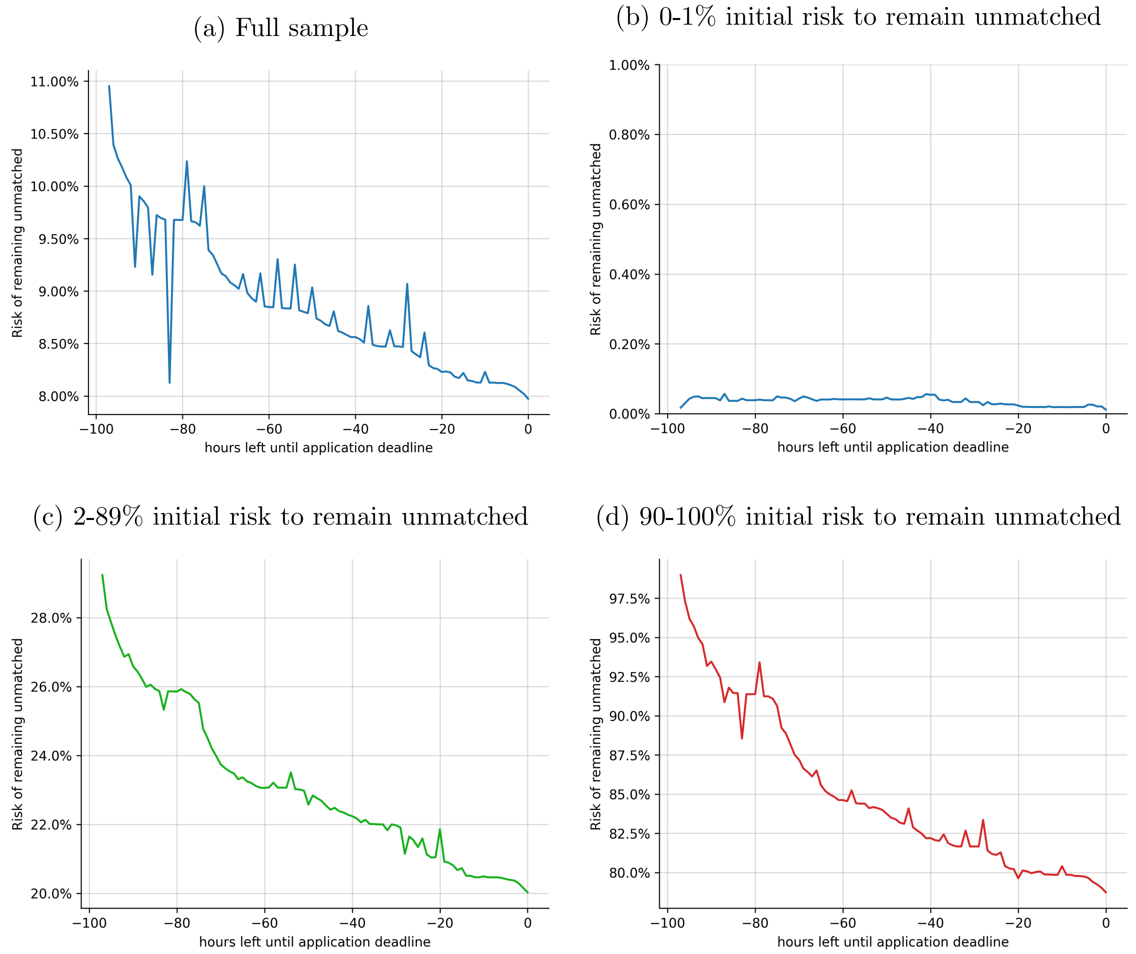
pp on average. The results for 2012, 2013 and 2014 are similar. Low-risk applicants' risk to remain unmatched remains largely constant while the risk of applicants with a high initial risk declines by 6 to 20 pp. Figures A21, A22 and A23 in the Appendix show the results for the other cohorts.

A decline in the risk of remaining unmatched can be driven by two types of application choices. First, applicants might extend their ROL by adding more programs, as long as the maximum length of 10 programs is not yet reached. As long as admission probability to a program is strictly positive, adding the program to the ROL reduces the risk to remain unmatched. Panel a) in Figure 13 shows that in aggregate applicants reduce the length of their ROL by about 1.2 programs on average. In 2012-2014 the decline is of similar magnitude (see Panel a) of Figures A24, A25 and A26). This aggregate trend is largely driven by applicants with a low initial risk to remain unmatched. Applicants with a 90-100% initial risk to remain unmatched slightly extend their ROL in 2015 (Panel d) of Figure 13), do not change the length of their ROL in 2014 and slightly shorten their ROL by about 0.5 programs in 2012 and 2013 (see Figures A24, A25 and A26) for all cohorts). Meanwhile, applicants with a low initial risk to remain unmatched shorten their ROL by about 1.5 programs in all four cohorts.

Although applicants tend to shorten their ROL, their risk to remain unmatched does not increase as shown in Figure 12 (other cohorts: Figures A21, A22 and A23). Applicants with a low initial risk to remain unmatched might have enough "safe" options to retain their low risk besides shortening their ROL. This is possible even if they drop some of their "safe" choices, as long as one "safe" option remains on their ROL. Applicants with a high initial risk to remain unmatched do not have that option. To avoid an increase in the risk to remain unmatched while shrinking their ROL, high-risk applicants have to replace programs with a low admission probability with higher-probability programs.

The second application choice that might drive the decline in applicants' risk to remain unmatched is exchanging ranked programs for programs with higher admission probability. Panel a) of Figure 14 shows how the average admission probability of programs

Figure 12: Average risk to remain unmatched over time, by initial risk (2015)

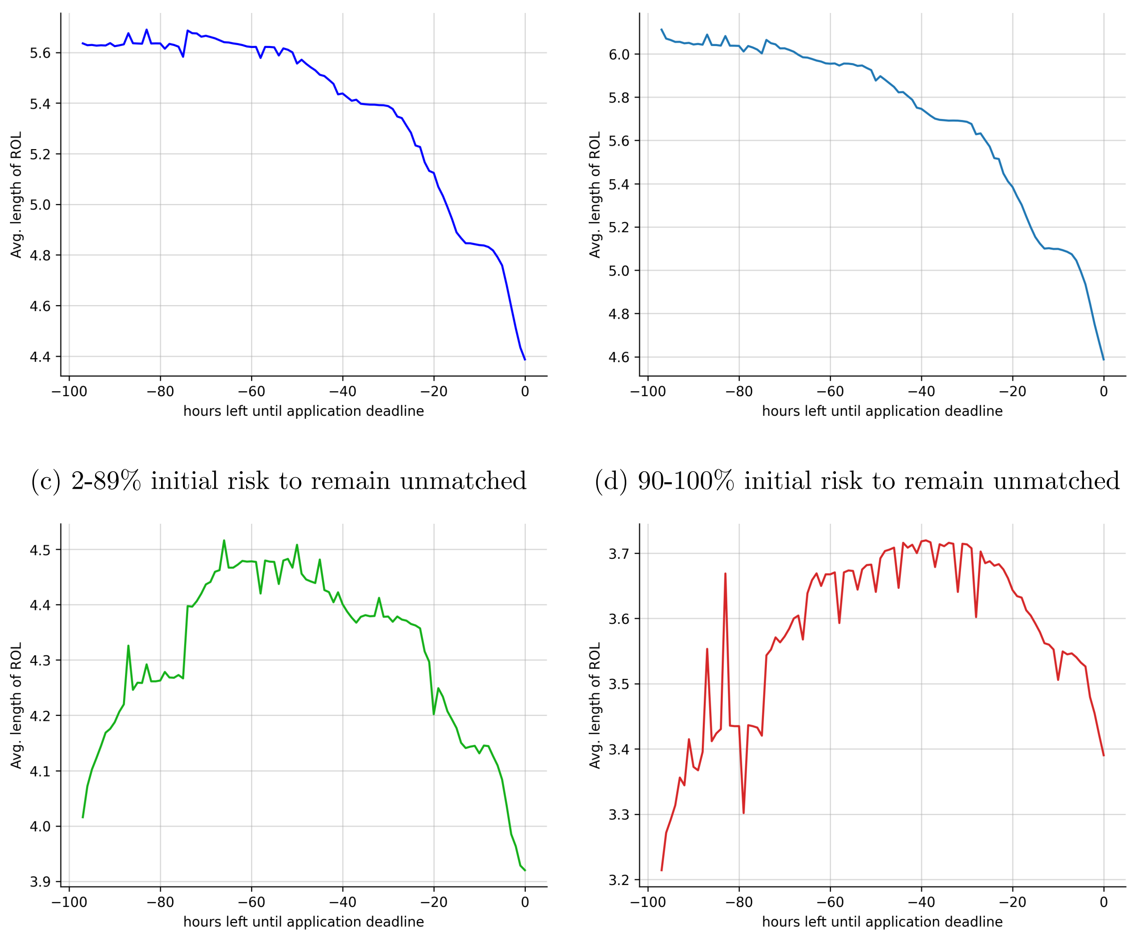


Note: Figure shows how the average risk to remain unmatched evolves over time for two subgroups. In Panel a) we show the average risk for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 80.8%, the group with an initial risk of 1-89% makes up 11.5% and the group with an initial risk of 90-100% makes up 7.7%.

on ranks 1-3 and on ranks 4-10 evolve over time. While the admission probability of programs on ranks 1-3 increases by 4.5 pp, admission probability of programs on ranks 4-10 decreases by about the same magnitude. The results are similar for 2012-2014, although the magnitude of change is lower in earlier years (see Figures A27, A28 and A29). Again, disaggregating the trend by initial risk to remain unmatched shows significant group differences (Panels b), c) and d) of Figure 14). While the behavioral pattern of low-risk applicants matches the aggregate pattern, applicants with a high initial risk to remain unmatched replace programs on all ranks with programs with higher admission probability. Admission probability to programs on ranks 1-3 increases from 0% to about 8%, that of programs on ranks 4-10 increases to 18% on average. Combined with Panel d) of Figure 13, this shows that for high-risk applicants the risk to remain unmatched declines largely due to exchanging low-probability with high-probability programs and particularly so for programs on lower ranks.

Another interesting finding from Figure 14 is that low-risk applicants seem to rank high-probability programs above programs with a lower admission probability. Assuming that applicants have a preference for more competitive programs, this application behavior

Figure 13: Average number of ranked programs over time, by initial risk (2015)



(a) Full sample

(b) 0-1% initial risk to remain unmatched

(c) 2-89% initial risk to remain unmatched

(d) 90-100% initial risk to remain unmatched

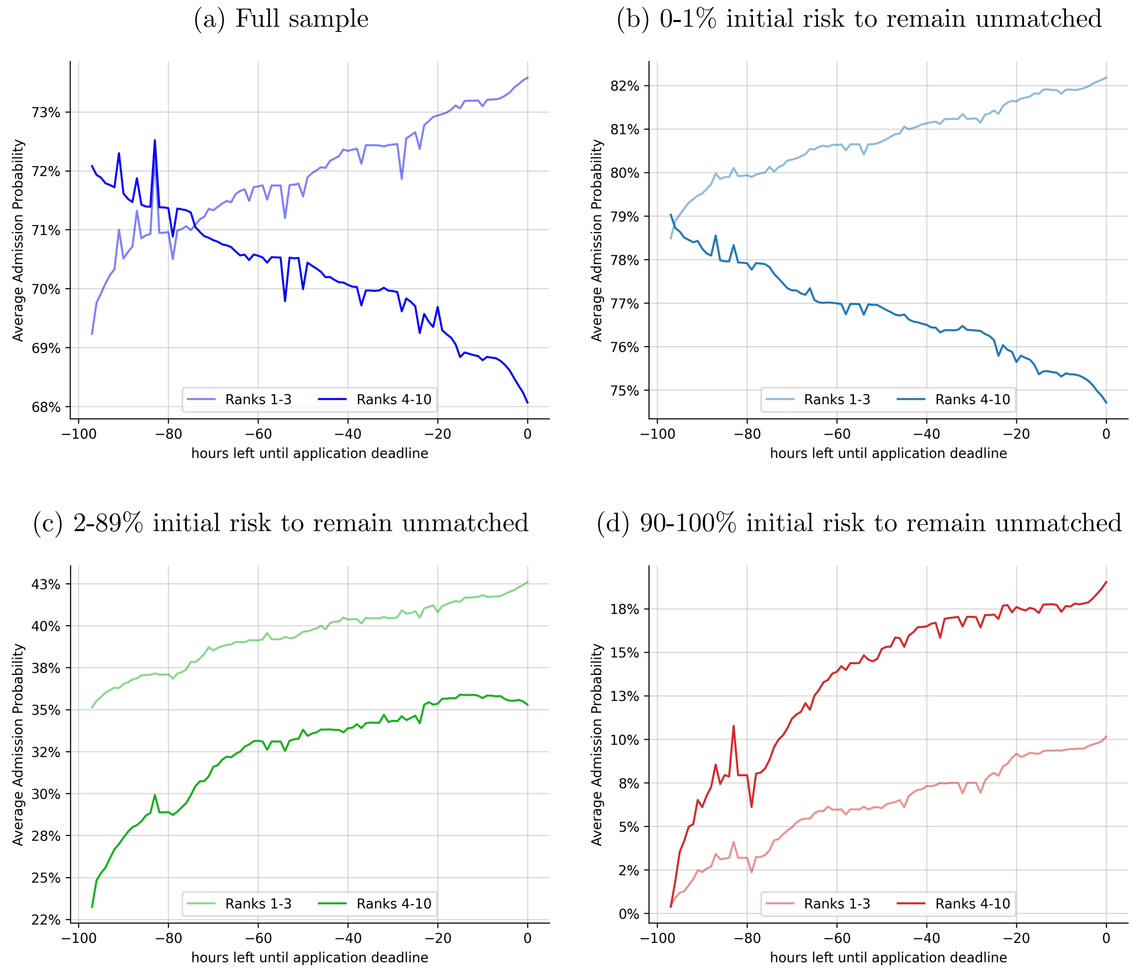
Note: Figure shows how the average number of ranked programs evolves over time for two subgroups. In Panel a) we show the average length of the ROL for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 80.8%, the group with an initial risk of 1-89% makes up 11.5% and the group with an initial risk of 90-100% makes up 7.7%.

is never optimal. As the gap in the average admission probability of programs on ranks 1-3 and 4-10 increases over time, receiving information signals on admission probability seems to exacerbate this strategic error. Of course, applicants might have a preference for program characteristics other than competitiveness but in this case we should not observe any pattern in average admission probability between higher- and lower-ranked programs.

Meanwhile, high-risk applicants follow the weakly dominant strategy by placing lower-probability programs on ranks 1-3 while filling lower ranks with safer options. Although they start with an average admission probability of approximately zero for all programs, this pattern emerges. In the context of the DA mechanism, this implies that applicants try for low-probability "reach" programs first and apply for safer options only in case they are not admitted to any of the higher-ranked programs.

Although the application choices of low-risk applicants are irrational in the framework of the canonical school choice model (Abdulkadiroğlu and Sönmez, 2003) and also under newer advances of the literature including incomplete preferences due to costly search (Artemov, 2021; Bucher and Caplin, 2021; Arteaga et al., 2022) and constrained choice (Calsamiglia et al., 2010; Ali and Shorrer, 2025), we are not the first to provide

Figure 14: Average admission probability over time, by initial risk (2015)



Note: Figure shows how the average admission probability of the three highest-ranked programs and of all lower-ranked programs evolves over time for two subgroups. In Panel a) we show the average admission probability for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 80.8%, the group with an initial risk of 1-89% makes up 11.5% and the group with an initial risk of 90-100% makes up 7.7%.

empirical evidence for applicants sorting programs by admission probability. Experiments show that 15-18% of applicants follow this application strategy (Pais and Pintér, 2008 and Y. Chen and Sönmez, 2006). Yet, in experiments it is particularly the high-risk applicants who sort programs by admission probability (Featherstone and Niederle, 2016) whereas in our case it is the low-risk applicants. Also in real-world applications of the DA mechanism applicants consider admission probability or their beliefs thereof when making their choices (Arteaga et al., 2022; Bobba and Frisancho, 2022; L. Chen and Pereyra, 2019; Larroucau et al., 2024; Shorrer and Sóvágó, 2023; Shorrer and Sóvágó, 2024). Rees-Jones and Shorrer (2023) suggest, among others, expectation-based loss aversion as an explanation for the observed application behavior.

6.2 Beliefs on admission probability and the initial ROL

In the previous analysis, we have to assume that applicants have a preference for competitive programs. For this reason we conclude from Figure 14 that the average applicant misrepresents their preferences by sorting programs by admission probability. In this section, we draw on survey data on applicants' true preferences and their expected admission probability thereto to study preference misrepresentation based on a more applicant-specific measure of preferences.

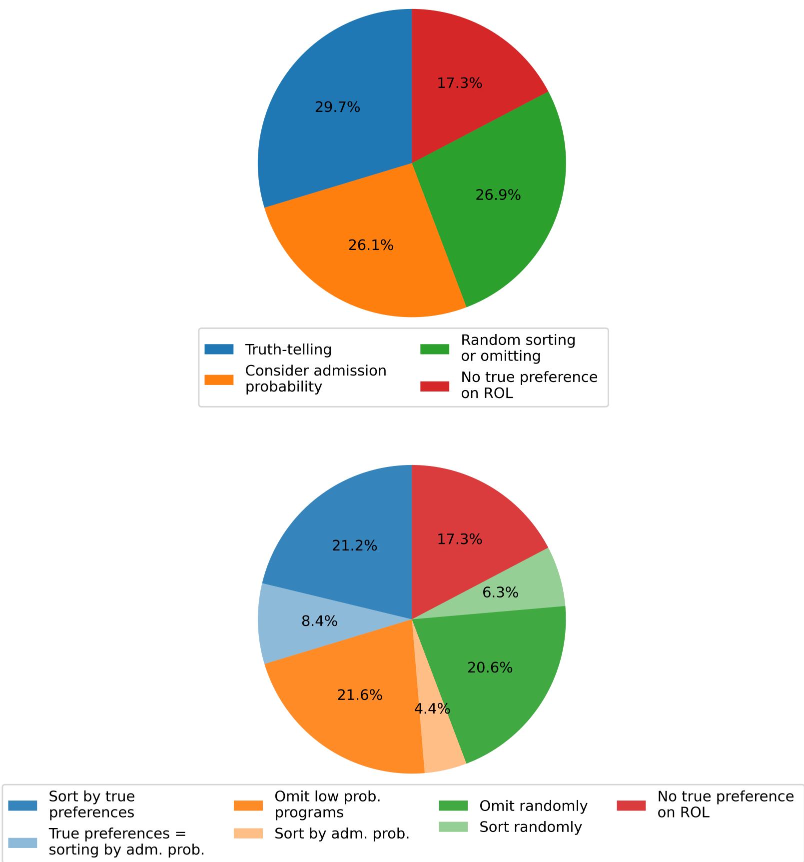
In 2019, applicants responded to the survey when first logging in to the application platform. This can be as early as January, when the application platform opens, but applicants might also register at a later time. At this time, although the application deadline is not due for long, applicants already (at least partly) established their preferences over study programs. This is because the registration for state exam subject tests closes in January. As some programs require the passing or weight the grade of non-mandatory subject tests, applicants should know about the admission requirements of study programs to which they want to apply. Thus, already in January, applicants should be (at least partially) informed about their preferences.

In our previous analyses we show that applicants adjust their application strategy to signals on admission probability. This could occur in two forms. First, applicants might consider admission probability in their choices, i.e., omitting zero or low-probability programs or sorting programs by admission probability. Second, the information signal on admission probability might encourage applicants to reevaluate their preferences by investing more search into feasible programs. For this reason, elicited survey preferences might not be stable over time. Yet, as applicants do not receive any signal on admission probability prior to submitting their initial ROL, reported survey preferences and expectations on admission probability should still be accurate at the beginning of the adjustment period.

Thus, we investigate to what extend survey preferences are reflected in the initial ROL and whether this is influenced by applicants' expected admission probability. To this end, we distinguish four groups of applicants: Applicants who we consider as "truth-telling" are those who have all of their reported survey preferences on their initial ROL and rank them in the order reported in the survey. Here, we allow applicants to rank their true preference in non-consecutive order as long as the ranking is kept in order. For example, an applicant might rank their most-preferred program first, a random program on rank 2 and their second- and third-most preferred program on ranks 3 and 4. This applicant would still be considered truth-telling. The second group of applicants are those who consider admission probability by either reordering their true preferences by their expected admission probability (in descending order) or by omitting programs with a lower expected admission probability. Again, for the former case, programs can be ordered non-consecutively as long as programs with a higher expected admission probability are ranked higher. For the latter case, we allow the minimum expected admission probability required for an applicant to rank a program on their initial ROL to differ between applicants. If all programs that an applicant omits have a strictly lower expected admission probability than all programs that the applicant ranks, the applicant is accounted to this group. The third group consists of applicants who either omit or reorder their reported survey preferences but not according to their expected admission probability. The pattern according to which they misrepresent their preferences in unobserved by us. We call this group "Random sorting and omitting". The last group of students rank none of their reported survey preferences on their initial ROL.

Due to the way in which we conducted the survey, a single survey preference is represented by multiple program IDs. We cannot distinguish highly similar programs (i.e., offered by the same faculty and with the same program name) with different program IDs. For our analysis this implies that if applicants apply to a highly similar program but e.g. with a different minor than their true preference, we consider them as applying to their true preference. Thus, we slightly loosen the definition of truth-telling. As a consequence of this, we observe that some applicants report the same program as their most, second-most and third-most preferred program. We classify these cases as applicants having only one survey preference. For these applicants it is enough to rank this one program ID on their initial ROL to be considered truth-telling. This implies that we likely over-estimate truth-telling in our results.

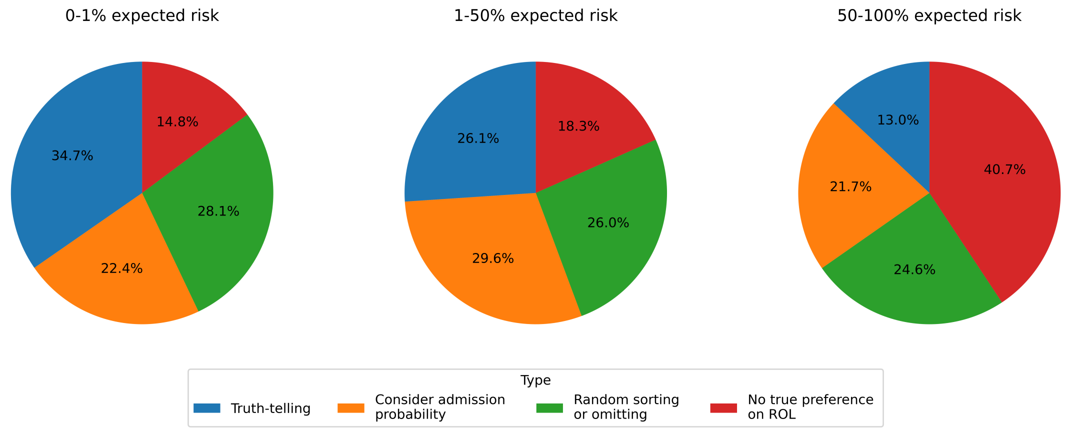
Figure 15: Strategic types



Note: Figure shows the distribution of applicants by their strategic type in the initial ROL compared to the reported survey preferences. We distinguish types by the way in which they deviate from their true survey preferences in their initial application choices.

Figure 15 shows the group shares. We find that 29.7% of applicants are "truth-telling", i.e., apply according to their reported true survey preferences in their initial ROL. With 26.1% the group of applicants whose innate belief on expected admission probability is reflected in their initial ROL is of similar size. Among those, the majority of applicants omits programs for which they expect admission probability to be low. Overall, only 4.4% of applicants sort programs by admission probability. The smallest group with 17.3% is the group of applicants who add none of their survey preferences on their ROL. Last, the remaining 26.9% of applicants misrepresent their preferences in a way unobserved by us. These applicants either omit some of their survey preferences but not necessarily those

Figure 16: Strategic groups, by expected risk to remain unmatched



Note: Figure shows the distribution of applicants by their strategic type in the initial ROL compared to the reported survey preferences. We distinguish types by the way in which they deviate from their true survey preferences in their initial application choices. We split applicants into three groups by their expected risk to remain unmatched to any of their survey preferences. This is computed using the expected admission probabilities to the top-3 most-preferred programs as reported in the survey.

with the lowest expected admission probability (20.6%) or sort their survey preferences to something other that expected admission probability (6.3%).

Additionally, we also split the group of ”truth-telling” applicants in two: those who apply according to their true preferences and by that forego sorting by expected admission probability and those whose reported true preferences are already sorted by expected admission probability. The latter group can thus sort programs by admission probability in the initial ROL while still applying according to their true preferences. With 8.4% the latter group is relatively small. Although we do not know the reason, this group of applicants seems to have a preference for safer programs.

Compared to experimental research, which reports truth-telling rates of 35 - 91.7%, the truth-telling rate we find in our real-life application of a DA is slightly below the lower bound (see Hakimov and Kübler (2021) for an overview of experiments). Still, our lower truth-telling rate is in line with the literature as truth-telling has been shown to decline in the complexity of the decision (Y. Chen et al., 2016; Y. Chen and Kesten, 2019; Pais and Pintér, 2008) and complexity in the Croatian setting with more than 700 study programs to choose from is arguably more complex than any of the experimental settings. While experiments find that 15-18% of applicants sort their choices by admission probability (Y. Chen et al., 2016; Y. Chen and Kesten, 2019; Pais and Pintér, 2008), ranking low-probability programs below more preferred programs with a higher admission probability, we find a significantly smaller share of applicants who follow this strategy. Still, the share of applicants in our setting who consider admission probability in their choices is significantly higher with 26.1%.

Last, we compare whether applicants expectation of remaining unmatched to their top-3 reported most preferred programs is related to the initial application choices we observe. To this end, we compute applicants risk to remain unmatched using the expected admission probability reported in the survey to their top-3 choices. We split applicants into three groups with 0-1%, 1-50% and 50-100% expected risk to remain unmatched.

Figure 16 shows that applicants with a high expected risk of not being matched to any of their top-3 survey preferences are less than half as likely to be truth-telling. Instead, 40% of these applicants have none of their reported preferences on their ROL. Meanwhile, 34% of applicants with a particularly low risk are truth-telling and only 14.8% have none of their reported true preferences on their initial ROL. The remaining strategies, considering admission probability and random sorting or omitting do not differ much between the three risk-groups. This finding supports the previous findings that beliefs about admission probability are reflected in strategic choices. A low risk to remain unmatched "allows" applicants to be truth-telling, while applicants with a high risk to remain unmatched might feel urged to reduce their risk by submitting a safer ROL.

Due to the design of the Croatian application system, applicants do not have to hedge risk in their initial ROL. As they can adjust their ROL at a later point, the risk to remain unmatched to any of their true preferences should not play a role for the initial application strategy. Yet, we observe this behavior.

7 Consequences of application strategies

In the previous sections we show mainly two types of application strategies that might result in suboptimal admission outcomes for applicants. First, Figure 14 shows that applicants sort programs by admission probability, on average ranking programs with higher admission probability on ranks 1-3 and programs with lower admission probability on lower ranks. This is particularly the case for applicants with a low risk to remain unmatched as shown in Figure 14. Due to this application choice, applicants might be admitted to a less competitive program than they could reach for. Second, Figure 15 shows that about 21% of applicants omit programs with a low expected admission probability. By this, they reduce their chance of being admitted to this program to zero.

In this section we investigate whether these strategic application choices are consequential. To this end, we successively adjust the two application strategies described above. Based on the adjusted ROLs we replicate the DA mechanism and compare to what extend the admission outcomes improve.

Here, we assume that applicants have a preference for more competitive programs, an assumption which is not uncommon in the literature.[5] In this, we disregard that applicants might have preferences for other characteristics such as the field of study or location. To partly address this, we restrict the set of programs based on which we construct the simulated ROLs to the programs applicants add to their ROL. By that, we ensure that applicants' preferences for other characteristics are reflected in our adjusted ROLs as we base the analysis on programs that applicants actually consider.

7.1 Sorting by admission probability

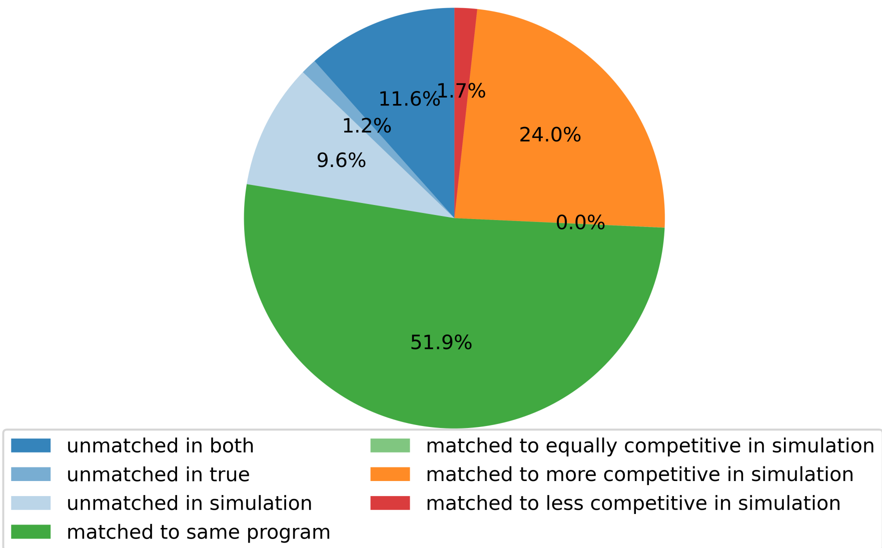
First, we correct the application strategy of sorting by admission probability. For this, we consider only the programs on applicants' final ROLs and thus respect applicants' final choice on the set of programs they want to apply to. To reverse the application strategy we sort programs by their admission probability but in ascending order. Under these adjusted ROLs, applicants apply to the most competitive programs first. Only if not admitted to any more competitive program, lower ranked programs are considered. As

[5]For example, Ali and Shorrer (2025) assume that applicants value programs with a low admission probability higher than less-competitive programs.

the set of programs on applicants' ROLs does not change, the risk to remain unmatched changes only due changes to other applicants' ROLs.

To evaluate the consequences of applicants applying to "safer" programs first, we compare the admission outcome of the simulated scenario to the original matchings observed in the data. Figure 17 shows how differences in admission outcomes are distributed in 2015. For the largest group of applicants the admission outcomes remain unchanged. This group includes the 51.9% of applicants who are matched to the same program, but also the 11.6% of applicants who are not matched to any ranked program under both scenarios. 24% of applicants improve their matching in the simulated scenario as they are now matched to a more competitive program. Meanwhile, 9.6% of applicants who were admitted under the original scenario are not admitted in our simulation. Their matching outcome worsens as higher scoring applicants who sort programs by admission probability in the observed scenario try for more competitive programs first under the simulated scenario.

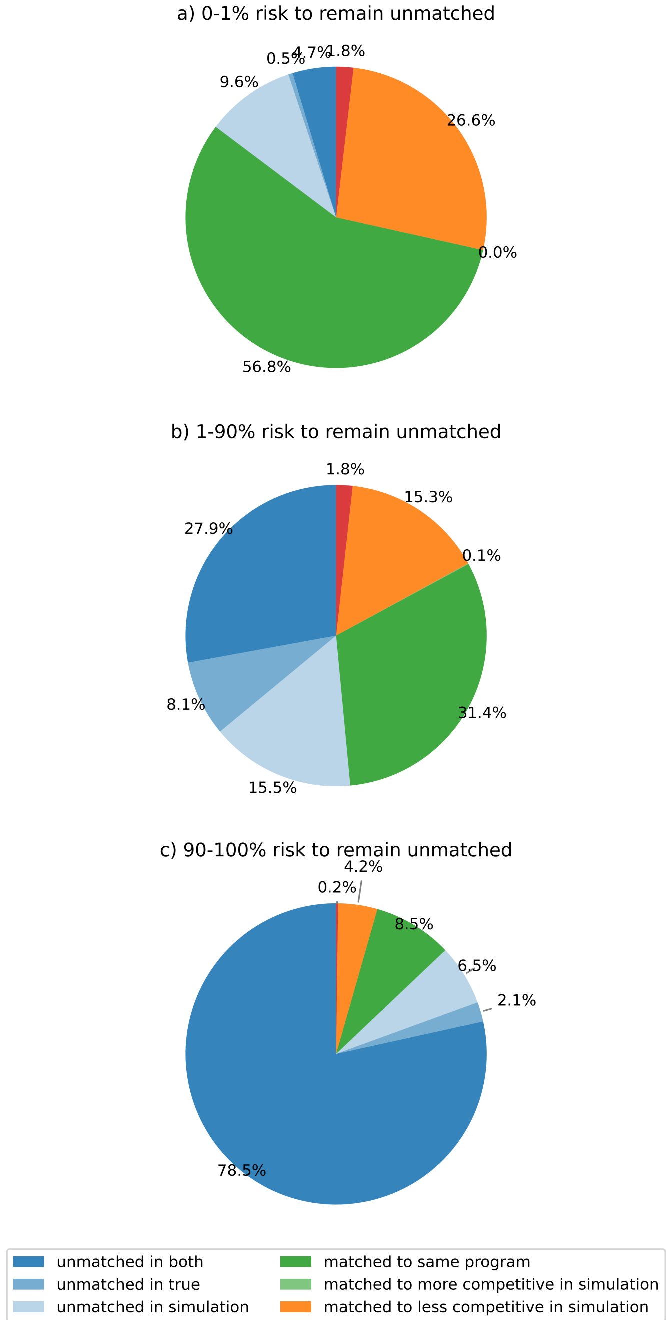
Figure 17: Admission outcome in the simulated vs. observed scenario



Note: Figure shows the shares of applicants by the type of change in their admission outcome due to following the adjusted application strategy. Here, the adjustment is a resorting of the final application choices by admission probability.

As Figure 14 shows that mostly applicants with a low initial risk to remain unmatched rank programs according to admission probability, we investigate changes in admission probability for applicants with a low and high initial risk to remain unmatched separately. Figure 18 shows the changes in admission outcomes for applicants with an initial risk to remain unmatched of 0-1%, 1-90% and 90-100% in Panels a), b) and c) respectively. While the large majority of high-risk applicants are unmatched under both scenarios, 26% of applicants with a low initial risk to remain unmatched could improve their matching outcome.

Figure 18: Admission outcome in the simulated vs. observed scenario, subgroups



Note: Figure shows the shares of applicants by the type of change in their admission outcome due to following the adjusted application strategy. Here, the adjustment is a resorting of the final application choices by admission probability. We show the results for three subgroups, with an initial risk to remain unmatched of 0-1%, 1-90% and 90-100%.

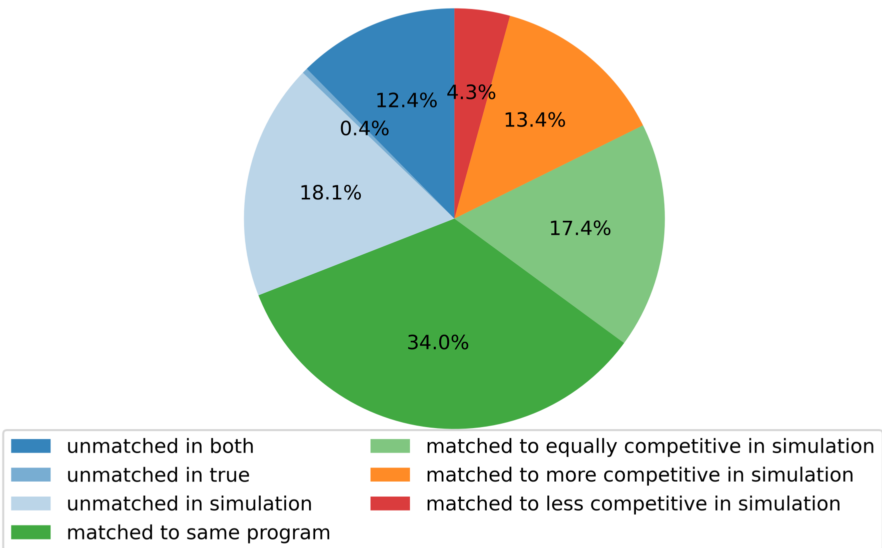
In the scenario we simulate, all applicants apply to the most competitive programs first. Thus, the changes in admission outcomes not only reflect adjustments in the application choices of single applicants. As other higher-scoring applicants consider more competitive programs first, admission probability to these programs declines for all other applicants. For this reason, some applicants who were previously admitted, are driven out. The results could look different if we would only consider the choice of a single applicant and other applicants' ROLs remain as they are in the original scenario.

7.2 Omitting programs with low admission probability

The second application strategy we address is omitting programs with low admission probability from the ROL completely. Also here, we only consider programs that applicants consider and by that respect applicants' preferences for other program characteristics. In contrast to the previous exercise we restrict the set of programs based on which we construct the adjusted ROL to programs that applicants *ever* add to any preliminary ROL. This follows the assumption that applicants add programs to their preliminary ROLs to learn about their admission probability thereto. After observing a low admission probability, some applicants might drop a program from their ROL. The results from our RDD analysis in Section 5 provide evidence for this behavior. Thus, applicants omit programs for which they have a preference from their ROL due to their perceived admission probability being low. By constructing a ROL based on all programs ever considered we correct this application strategy. Here, we disregard that applicants might not add programs for which they expect admission probability to be zero. For these programs, applicants might not consider it worth even trying. Thus, also our adjusted ROL reflects beliefs on admission probability to some extend.

To construct the adjusted ROL we sort all programs an applicant ever considers by admission probability in ascending order. As applicants can rank at most 10 programs, we truncate the program ranking of each applicant at 10, such that each simulated ROL consists of the (at most) 10 most competitive programs the applicant ever considers. This implies that the adjusted ROL is the most risky ROL that can be constructed from applicants revealed preferences.

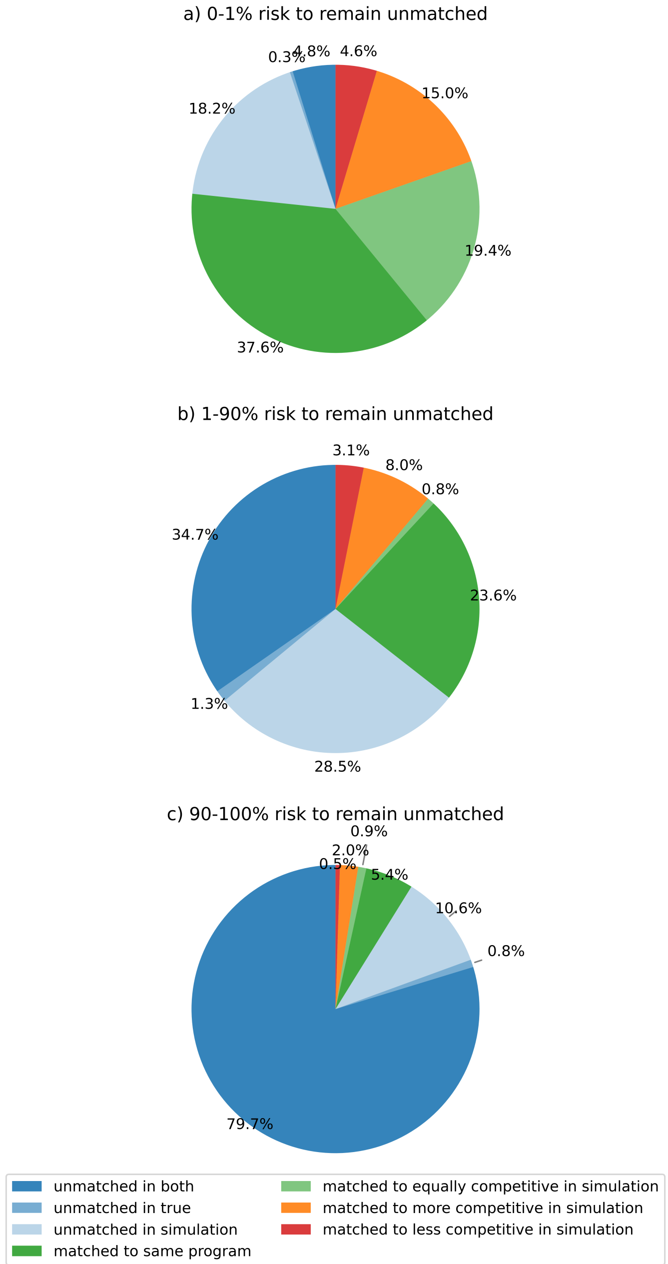
Figure 19: Admission outcome in the simulated vs. observed scenario



Note: Figure shows the shares of applicants by the type of change in their admission outcome due to following the adjusted application strategy. Here, the adjustment is applying to the ten most competitive programs ever considered in the adjustment period.

Figure 19 shows that while more than 50% of applicants do not change their admission outcome in terms of competitiveness of the matched program, 13.4% of applicants can improve their application choices under a more risky application strategy. Yet, with 18.1%, the share of applicants who are not matched to any ranked program under the simulated scenario is even higher. In contrast to the previously simulated scenario, this share is now not only driven by other applicants choices but also by the more risky choices of each single applicant. Overall, Figure 19 shows that the average applicant does not benefit from applying only to the most preferred (most competitive) study programs if preferences are based solely on competitiveness.

Figure 20: Admission outcome in the simulated vs. observed scenario, subgroups



Note: Figure shows the shares of applicants by the type of change in their admission outcome due to following the adjusted application strategy. Here, the adjustment is applying to the ten most competitive programs ever considered in the adjustment period. We show the results for three subgroups, with an initial risk to remain unmatched of 0-1%, 1-90% and 90-100%.

Also for this simulated scenario we conduct a subgroup analysis, the results of which are shown in Figure 20. Applicants with a low initial risk to remain unmatched benefit more from more risky application choices as 15% of this group can improve their matching. Still, an even larger fraction of this group remains unmatched to any program under our simulated scenario although they are admitted under the observed scenario with 18.2% of applicants affected by this. Thus, it is recommendable to add at least some safe programs to the ROL. Meanwhile, the admission outcome of most applicants with a high initial risk to remain unmatched does not change. About 80% of applicants in this group are not admitted to any program under both scenarios and further 5.4% are admitted to the same program. Yet, also for this group, 10.6% of applicants who would be matched under the original scenario are not matched in our simulation.

Jointly, these findings show that the majority of applicants is not harmed and about a quarter of applicants benefits from applying to risky choices first. Yet, applying only to the most risky of one's preferred programs can result in not being admitted at all. Thus, in line with the theory of portfolio choice (Ali and Shorrer, 2025), applying to risky options first and adding safe options at lower ranks seems like the optimal strategy under constrained choice.

8 Conclusion

In our study, we investigate the role of beliefs about admission probability for college application strategies in a repeated DA setting in Croatia. Here, applicants receive hourly information signals on admission probability, while they can still adjust their application choices. Over time, they develop their final and binding application strategies. Observing the information signals and strategic adjustments, we investigate how changing beliefs on admission probability are reflected in within-applicant changes to application choices.

In four parts, we show that applicants consider their beliefs about admission probability when deciding on the study programs to which they want to apply. First, we provide descriptive evidence on the dynamics of the repeated DA induced by strategic adjustments by applicants. Programs' cutoff scores fluctuate, resulting in hourly changes in the preliminary admission outcomes and in the information signals on admission probability that applicants receive via the system. This volatility differs between programs in frequency and magnitude. Programs with a larger quota experience more fluctuations of smaller magnitude than programs with a smaller quota.

Second, exploiting the RDD setting of a sharp (preliminary) admission cutoff, we show that applicants' subjective beliefs about admission probability feed into their application strategy. Applicants who receive a positive preliminary signal on admission probability are less likely to adjust their application choices than applicants who receive a negative preliminary signal. Compared to the baseline, the probability of changing for applicants who receive a negative signal is more than 11-23% higher than for applicants who receive a positive signal on admission probability. In particular, applicants who receive a negative preliminary signal on admission probability are more likely to delete the affected program.

Third, we show how applicants develop their final application strategy over time and in particular how this differs between applicants with a high and low initial risk of not being admitted to any of their ranked programs. Applicants with a high initial risk to remain unmatched improve their application choices over time and by that reduce this risk by up to 20 pp on average. They achieve this by swapping programs with a low admission probability for less risky programs. Meanwhile, applicants with a low initial risk to remain unmatched shorten their ROL over time and sort programs by admission probability. Although these adjustments do not affect their risk of remaining unmatched, sorting by admission probability might result in being matched to a less competitive program.

Next, we use survey data on the most preferred programs of the applicants and their expected admission probability to identify application strategies in initial application choices. We show that the initial ROL already reflects the beliefs of the applicants about admission probability, with 26% of the applicants omitting programs with lower expected admission probability or sorting the programs by admission probability.

Finally, we quantify the consequences of two potentially harmful application strategies that we identified in the previous sections by re-running the repeated DA mechanism based on alternative application choices. First, we correct the application behavior of sorting by admission probability. Assuming that applicants prefer more competitive programs, simply resorting the final ROL of applicants improves the admission result of 24% of applicants. Second, we reverse the application behavior of omitting programs with low admission probability. We construct for each applicant the most risky ROL from the set of programs they ever consider. Applying to the most risky ROL can lead to an improved match for 13.4% of applicants. However, 18.1% of the applicants benefit from adding a safety program with a higher admission probability to their ROL. These applicants remain unmatched to any program on the simulated risky ROL while they find a match with their observed application choices.

With our research, we contribute to the limited empirical literature on application strategies in real-world applications of DA mechanisms. The unique setting in Croatia allows us to exploit within-applicant changes in application behavior and show how application choices are affected by beliefs on admission probability. To our knowledge, we are among the first to quantify strategic choices for the entire universe of applicants on a repeated DA system. Our findings are relevant for the more commonly applied static DA as well. Although applicants receive precise and applicant-specific information on admission probabilities, they make suboptimal choices. In a static DA, in which applicants do not have access to this precise information, any application strategy based on inaccurate beliefs on admission probability is likely even more detrimental than we observe for the repeated DA.

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A Appendix

A.1 Volatility in program cutoffs

Figure A1: Cutoff score fluctuations over time (relative to the final cutoff)

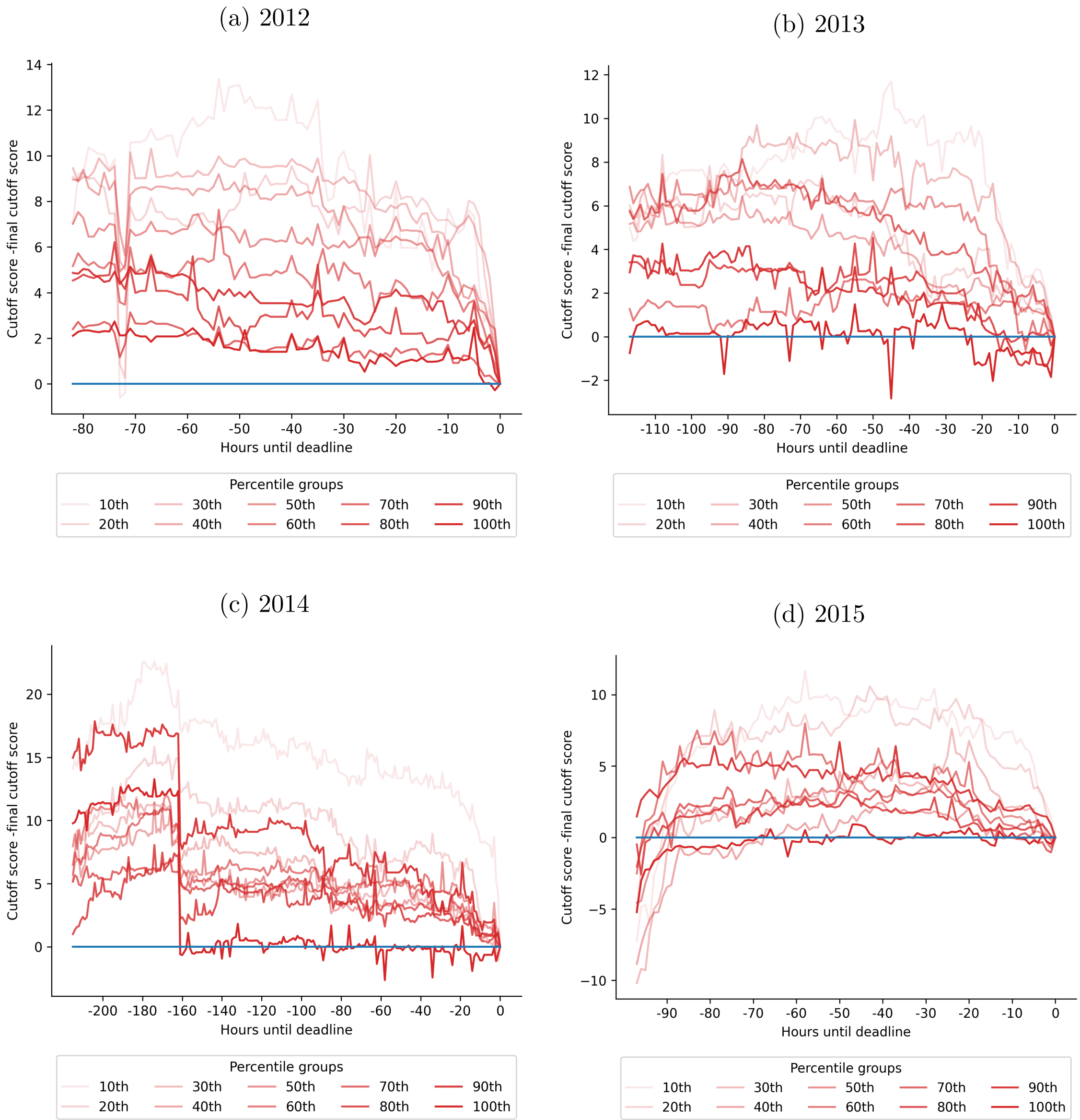


Figure A2: Initial and final cutoff scores

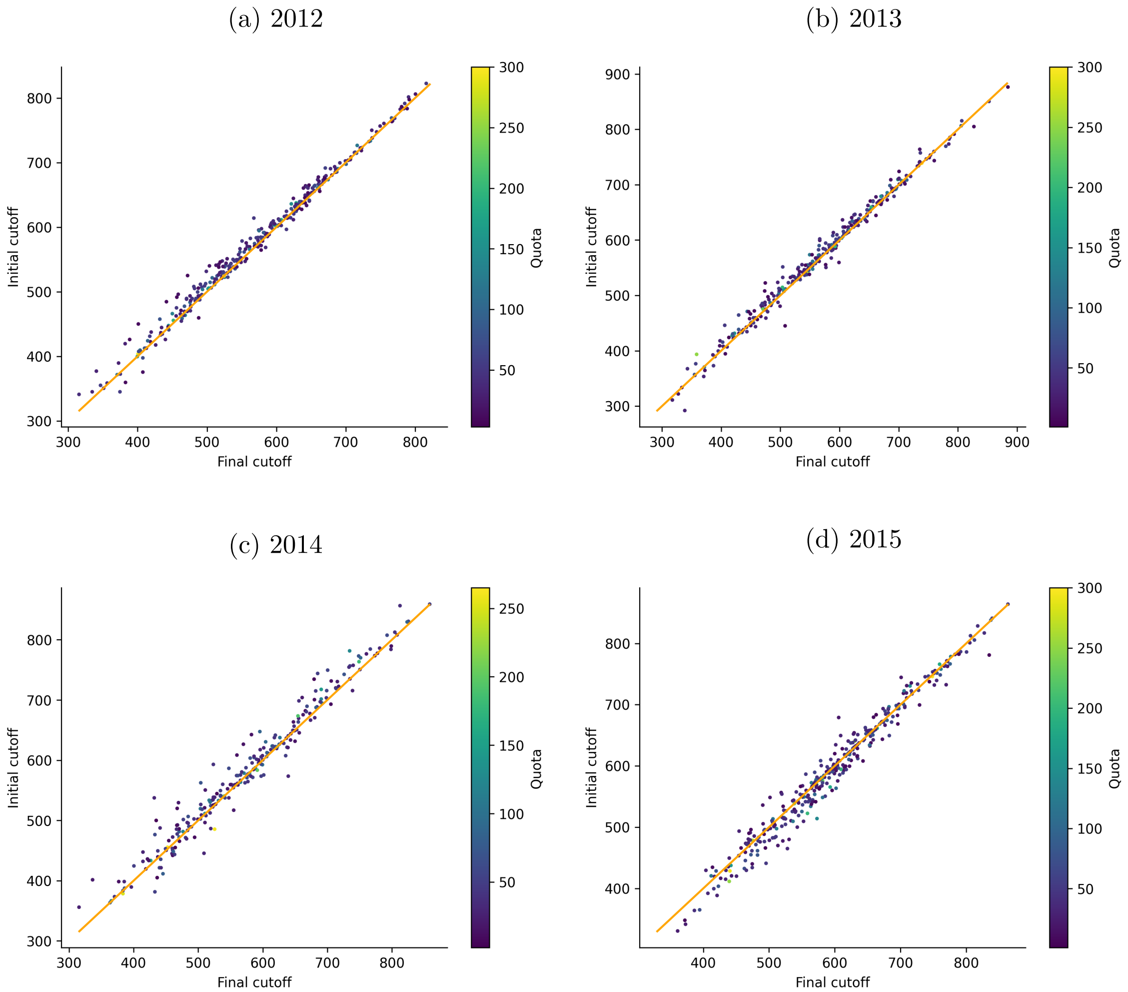


Figure A3: Distribution of programs by number of fluctuations

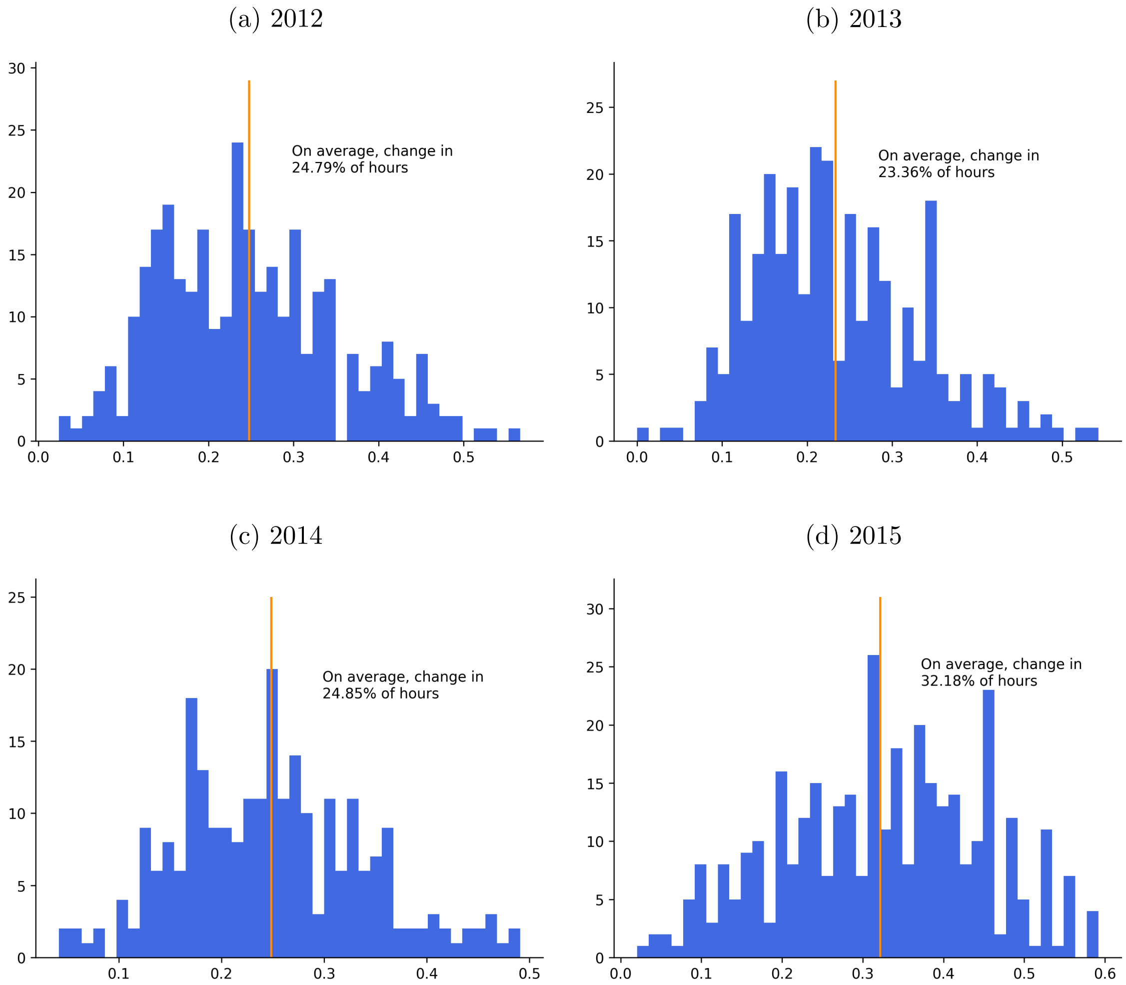


Figure A4: Distribution of programs by avg. magnitude of fluctuations

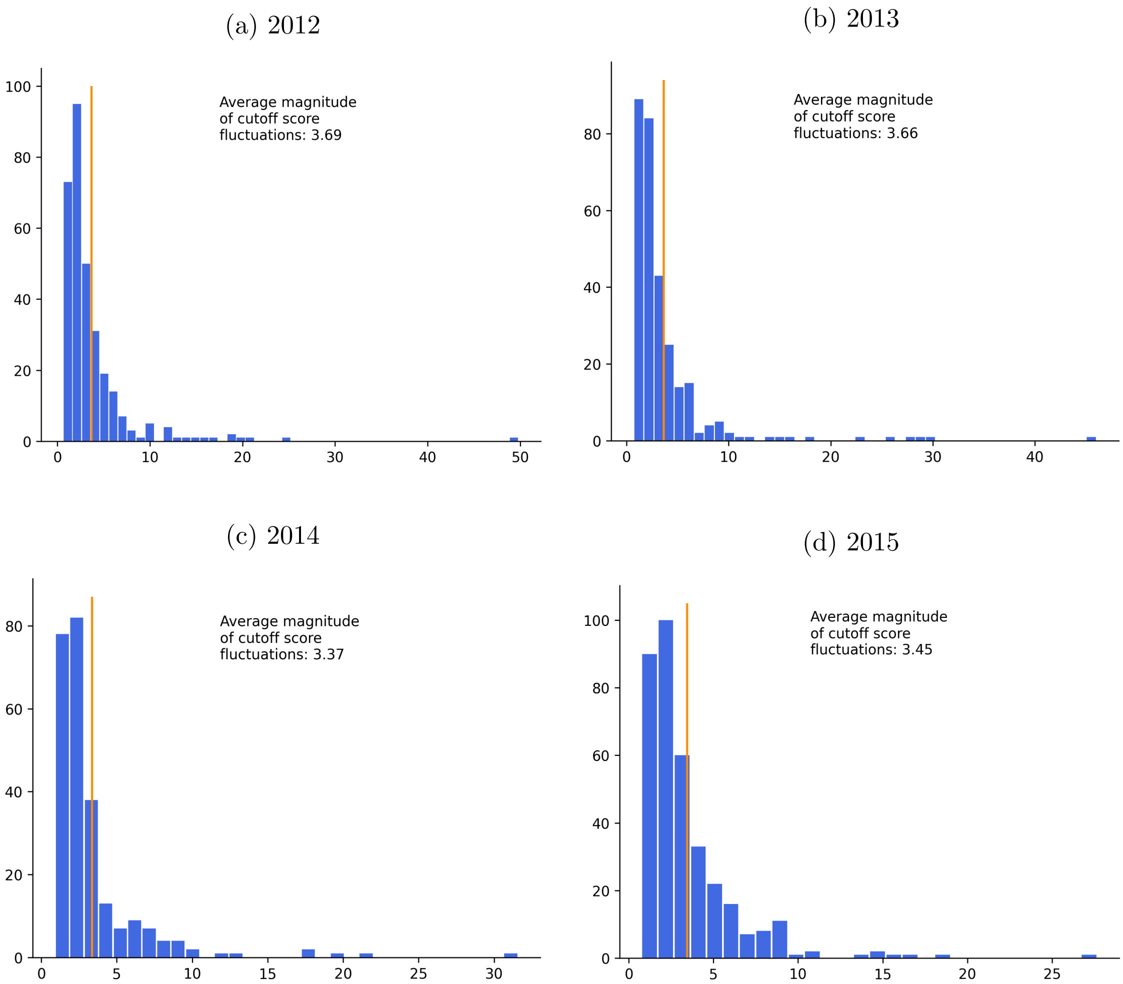
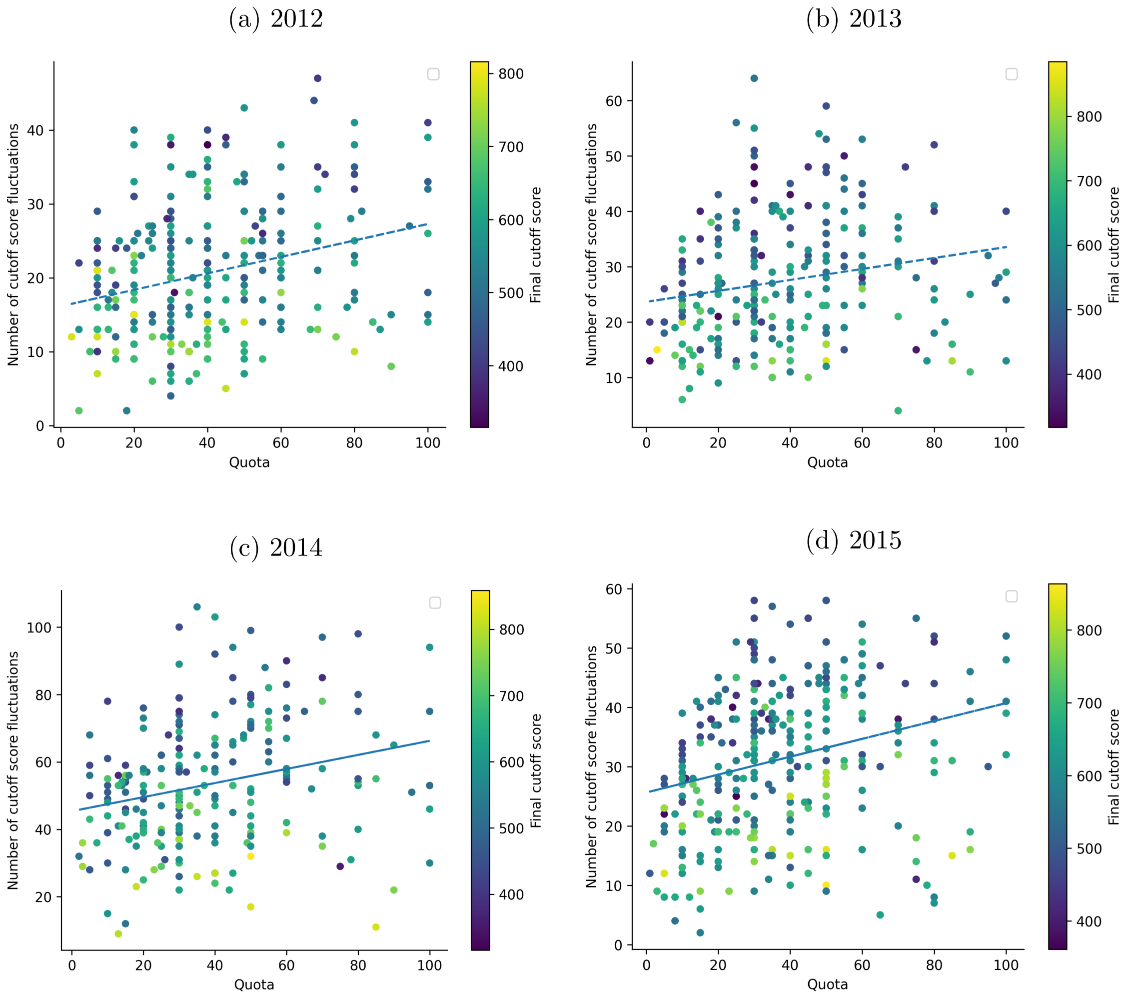


Figure A5: Number of fluctuations by program characteristics



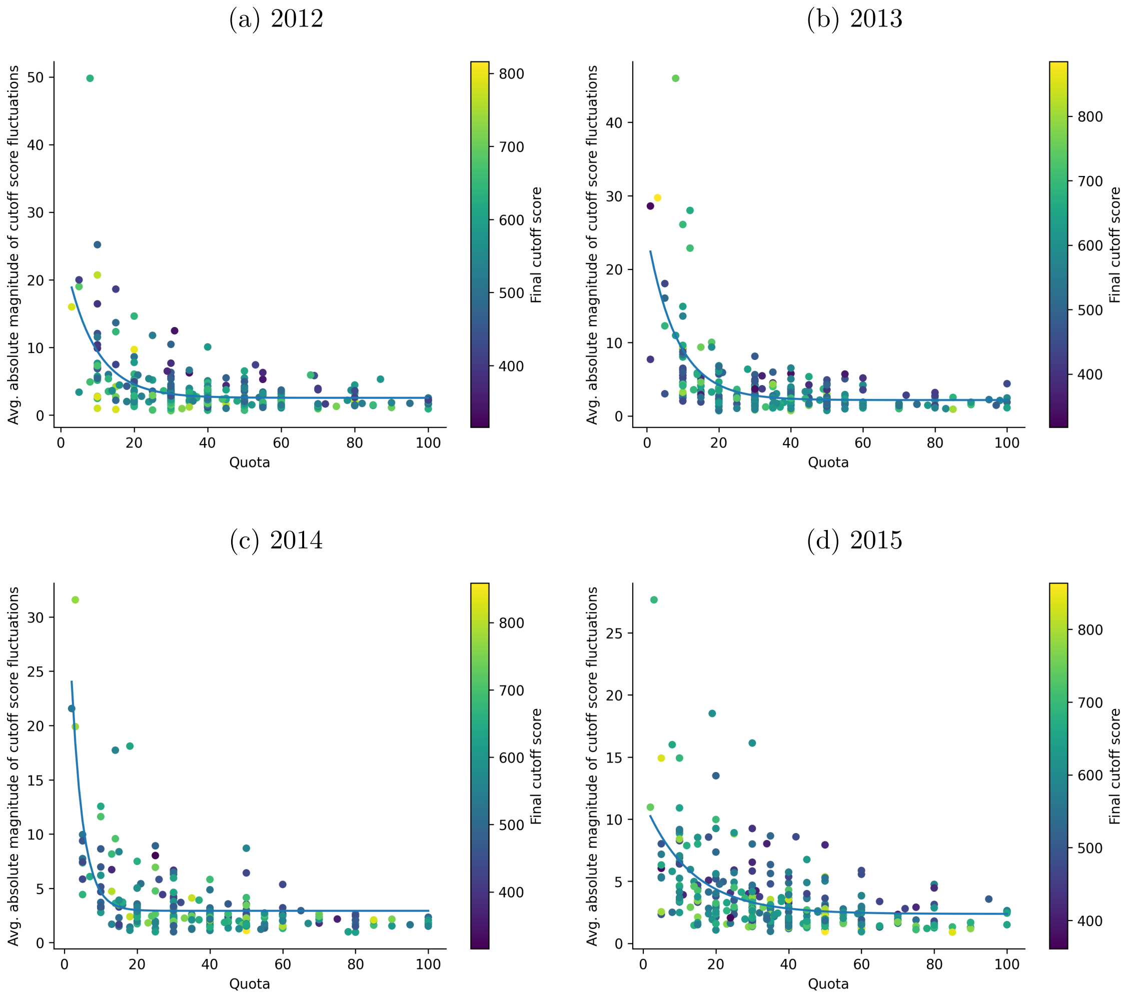
(a) 2012

(b) 2013

(c) 2014

(d) 2015

Figure A6: Magnitude of fluctuations by program characteristics



A.2 Data

Table A1: Data Summary

	2012	2013	2014	2015
Panel a) Timing				
publish SE results	9.7.	9.7.	7.7.	13.7.
end of complaints	12.7.	12.7.	14.7.	15.7.
application deadline	17.7. 00am	17.7. 12am	17.7. 12pm	17.7.4pm
Panel b) Overdemand				
# programs	717	748	762	773
w/o overdemand	305	435	440	436
with overdemand	412	313	322	337
avg. overdemand	62.3	49.9	56.1	69.4
median	43	35	39	46
25th pctl.	19	15	17	20
75th pctl.	81	64	77	92
Panel c) Direction of cutoff score fluctuations				
decrease	222	183	161	196
constant	25	33	22	18
increase	66	80	62	134

Note: In this table we summarize main characteristics of the data. Panel a) shows the dates of the beginning and end of the adjustment period in each year. Panel b) shows the number of programs with and without overdemand and the extend of overdemand. Panel c) shows the number of programs by the direction of cutoff score changes from the beginning to the end of the adjustment period.

A.3 RDD

A.3.1 RDD samples by bandwidth

Table A2: Summary statistics RDD sample

2012	10%	20%	30%	10% RDD	20% RDD	30% RDD
Min. point distance	-11.62	-23.30	-34.71	-8.36	-18.40	-28.75
Max. point distance	14.59	23.78	32.94	10.84	19.72	28.33
Min. rank distance	-5.20	-10.67	-15.94	-5.11	-10.35	-15.44
Max. rank distance	5.22	10.67	15.96	5.09	10.43	15.65
Avg. adm.prob. below	0.62	0.54	0.48	0.59	0.51	0.44
Avg. adm.prob. above	0.79	0.83	0.86	0.77	0.82	0.86
2013	10%	20%	30%	10% RDD	20% RDD	30% RDD
Min. point distance	-10.90	-21.62	-31.95	-6.59	-15.95	-25.03
Max. point distance	15.11	24.77	33.42	9.28	17.13	25.34
Min. rank distance	-4.95	-10.15	-14.98	-4.68	-9.72	-14.32
Max. rank distance	4.99	10.25	15.29	4.78	9.92	14.96
Avg. adm.prob. below	0.78	0.72	0.66	0.74	0.67	0.62
Avg. adm.prob. above	0.88	0.90	0.92	0.86	0.90	0.91
2014	10%	20%	30%	10% RDD	20% RDD	30% RDD
Min. point distance	-12.88	-24.74	-34.86	-7.82	-17.15	-26.23
Max. point distance	16.23	26.21	35.47	9.37	18.13	26.65
Min. rank distance	-5.17	-10.61	-15.66	-4.97	-9.99	-14.62
Max. rank distance	5.18	10.65	15.91	5.14	10.37	15.62
Avg. adm.prob. below	0.67	0.60	0.55	0.59	0.51	0.44
Avg. adm.prob. above	0.82	0.86	0.89	0.79	0.84	0.87
2015	10%	20%	30%	10% RDD	20% RDD	30% RDD
Min. point distance	-12.49	-24.13	-34.18	-6.71	-16.53	-25.16
Max. point distance	15.89	26.28	35.67	9.54	18.25	26.50
Min. rank distance	-5.08	-10.48	-15.60	-4.90	-10.13	-15.01
Max. rank distance	5.08	10.49	15.67	5.00	10.32	15.47
Avg. adm.prob. below	0.96	0.94	0.93	0.97	0.95	0.93
Avg. adm.prob. above	0.97	0.98	0.98	0.98	0.98	0.98

Note: In this table we show the range of scores, rank positions and admission probability in each of six samples. To compute the minimum point distance we take for each program the lowest score within the sample and subtract the cutoff. We show the average admission probability of applicants above and below the cutoff. The samples in Columns (1)-(3) are restricted only by the relative rank distance i.e., 10, 20 or 30% of the quota. The samples in Columns (4)-(6) are additionally restricted to the last 10 hours of the adjustment period and to applicants' highest ranked programs. These are the samples we use for the RDD regressions.

Table A3: Information signals and Probability to change, 2012

	Dep. var.: 1[Change] × 100		
	Point distance	Rank distance	Above/Below
(1)	(2)	(3)	
Distance	-0.0017***	-0.0013***	-0.3572***
	(0.0002)	(0.0002)	(0.0338)
Constant	3.9212***	3.9117***	4.1030***
	(0.0169)	(0.0169)	(0.0247)
Program FE	No	No	No
Observations	1,324,032	1,324,032	1,324,032
R-squared	0.0001	0.0001	0.0001

Note: Table shows the coefficients of regressing three different types of information signals on a dichotomous variable that equals 1 if an applicant changes a program at time t. The information signal in Column 1 is the distance to the cutoff in terms of points. Below the cutoff, the distance is negative, above the cutoff it is positive. The coefficient of -0.00003 means that as applicants below the cutoff move closer to the cutoff and applicants above the cutoff move further away by one point, the probability to change declines by 0.003 pp. Similarly, the information signal in Column 2 is the rank distance to the cutoff. In Column 3 the information signal is dichotomous and equal to 1 if an applicant is above the cutoff and zero otherwise. Applicants above the cutoff are 0.65pp less likely to adjust their ROL. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A4: Information signals and Probability to change, 2013

	Dep. var.: 1[Change] × 100		
	Point distance	Rank distance	Above/Below
(1)	(2)	(3)	
Distance	-0.0018***	-0.0016***	-0.3560***
	(0.0002)	(0.0001)	(0.0292)
Constant	3.8520***	3.8342***	4.0315***
	(0.0146)	(0.0147)	(0.0210)
Program FE	No	No	No
Observations	1,736,721	1,736,721	1,736,730
R-squared	0.0001	0.0001	0.0001

Note: Table shows the coefficients of regressing three different types of information signals on a dichotomous variable that equals 1 if an applicant changes a program at time t. The information signal in Column 1 is the distance to the cutoff in terms of points. Below the cutoff, the distance is negative, above the cutoff it is positive. The coefficient of -0.00003 means that as applicants below the cutoff move closer to the cutoff and applicants above the cutoff move further away by one point, the probability to change declines by 0.003 pp. Similarly, the information signal in Column 2 is the rank distance to the cutoff. In Column 3 the information signal is dichotomous and equal to 1 if an applicant is above the cutoff and zero otherwise. Applicants above the cutoff are 0.65pp less likely to adjust their ROL. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A5: Information signals and Probability to change, 2014

	Dep. var.: 1[Change] $\times$ 100		
	Point distance	Rank distance	Above/Below
(1)	(2)	(3)	
Distance	-0.0013***	-0.0009***	-0.2484***
	(0.0001)	(0.0001)	(0.0246)
Constant	4.6266***	4.6213***	4.7532***
	(0.0123)	(0.0124)	(0.0172)
Program FE	No	No	No
Observations	2,917,368	2,917,368	2,917,368
R-squared	0.0000	0.0000	0.0000

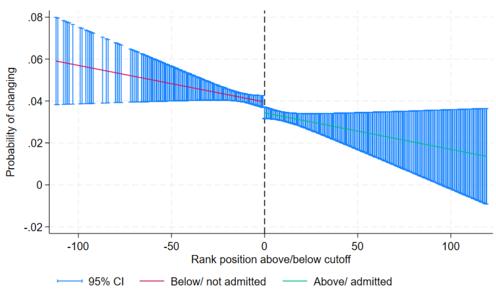
Note: Table shows the coefficients of regressing three different types of information signals on a dichotomous variable that equals 1 if an applicant changes a program at time t. The information signal in Column 1 is the distance to the cutoff in terms of points. Below the cutoff, the distance is negative, above the cutoff it is positive. The coefficient of -0.00003 means that as applicants below the cutoff move closer to the cutoff and applicants above the cutoff move further away by one point, the probability to change declines by 0.003 pp. Similarly, the information signal in Column 2 is the rank distance to the cutoff. In Column 3 the information signal is dichotomous and equal to 1 if an applicant is above the cutoff and zero otherwise. Applicants above the cutoff are 0.65pp less likely to adjust their ROL. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

A.3.2 Reduced form

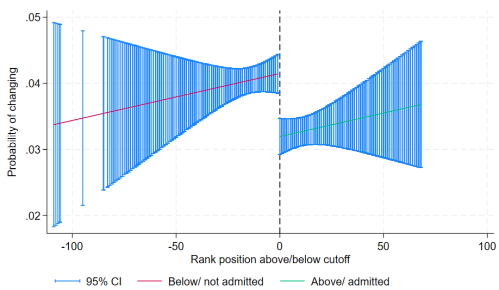
A.3.3 RDD plots

Figure A7: RDD, bw=20%, running variable = rank distance

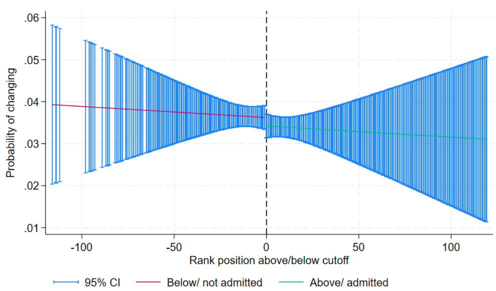
(a) 2012



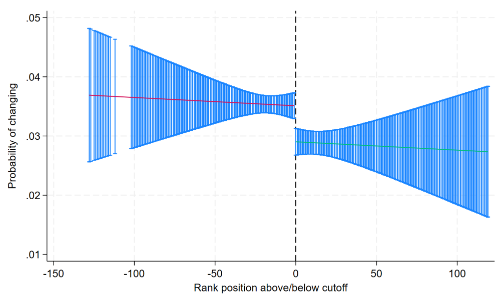
(b) 2013



(c) 2014



(d) 2015



A.3.4 RDD results

Table A6: Distance to cutoff and Probability to change, bandwidth = 0.1, 2012

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.769**	-0.667*	0.167	0.870	-1.165	0.013
	(0.368)	(0.349)	(0.881)	(1.151)	(1.494)	(1.728)
Distance	-0.001	0.003	-0.020	-0.072	0.161*	0.129
	(0.017)	(0.021)	(0.046)	(0.070)	(0.084)	(0.115)
Constant	4.063		6.735		9.472	
Program FE	No	Yes	No	Yes	No	Yes
Observations	18,646	18,646	6,489	6,489	2,807	2,807
# Programs		306		266		210
R-squared	0.0004	0.0002	0.0000	0.0003	0.0014	0.0008

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A7: Distance to cutoff and Probability to change, bandwidth = 0.1, 2013

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.978**	-0.860**	0.016	0.270	-0.303	0.061
	(0.399)	(0.408)	(0.721)	(0.843)	(1.191)	(1.623)
Distance	0.014	0.003	0.050*	0.020	-0.014	-0.040
	(0.021)	(0.027)	(0.028)	(0.029)	(0.062)	(0.064)
Constant	4.216		4.383		4.947	
Program FE	No	Yes	No	Yes	No	Yes
Observations	18,691	18,691	6,070	6,070	2,875	2,875
# Programs		282		222		175
R-squared	0.0005	0.0004	0.0007	0.0001	0.0001	0.0001

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A8: Distance to cutoff and Probability to change, bandwidth = 0.1, 2014

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	0.197	0.248	-0.224	0.395	-0.594	-1.088
	(0.372)	(0.383)	(0.741)	(0.866)	(1.301)	(1.806)
Distance	-0.025	-0.037*	0.022	-0.021	0.034	0.030
	(0.019)	(0.020)	(0.030)	(0.034)	(0.063)	(0.094)
Constant	3.343		4.507		5.471	
Program FE	No	Yes	No	Yes	No	Yes
Observations	17,503	17,503	5,688	5,688	2,325	2,325
# Programs		238		190		150
R-squared	0.0001	0.0002	0.0001	0.0000	0.0001	0.0001

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A9: Distance to cutoff and Probability to change, bandwidth = 0.1, 2015

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.451	-0.327	-1.288**	-1.245*	-2.424***	-3.000***
	(0.293)	(0.324)	(0.585)	(0.675)	(0.908)	(1.096)
Distance	-0.002	-0.001	0.061***	0.056**	0.094***	0.084
	(0.013)	(0.014)	(0.021)	(0.023)	(0.034)	(0.057)
Constant	3.289		5.473		6.398	
Program FE	No	Yes	No	Yes	No	Yes
Observations	25,615	25,615	9,486	9,486	4,547	4,547
# Programs		344		294		239
R-squared	0.0002	0.0001	0.0008	0.0005	0.0017	0.0016

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A10: Distance to cutoff and Probability to change, bandwidth = 0.2, 2012

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.601**	-0.519*	0.527	0.459	0.075	-0.034
	(0.265)	(0.292)	(0.579)	(0.662)	(0.982)	(1.226)
Distance	-0.017**	-0.017*	-0.014	-0.021	0.047*	0.055
	(0.007)	(0.010)	(0.014)	(0.017)	(0.025)	(0.037)
Constant	3.997		6.245		8.476	
Program FE	No	Yes	No	Yes	No	Yes
Observations	36,294	36,294	13,510	13,510	6,293	6,293
# Programs		311		291		253
R-squared	0.0009	0.0006	0.0001	0.0001	0.0010	0.0007

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A11: Distance to cutoff and Probability to change, bandwidth = 0.2, 2013

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.902***	-0.955***	-0.236	0.004	-1.036	-0.065
	(0.291)	(0.294)	(0.494)	(0.598)	(0.754)	(0.977)
Distance	0.009	0.007	0.022**	0.006	0.039**	0.015
	(0.009)	(0.008)	(0.011)	(0.017)	(0.017)	(0.020)
Constant	4.129		4.389		5.5	
Program FE	No	Yes	No	Yes	No	Yes
Observations	35,870	35,870	12,757	12,757	6,136	6,136
# Programs		288		258		222
R-squared	0.0004	0.0004	0.0004	0.0000	0.0006	0.0001

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A12: Distance to cutoff and Probability to change, bandwidth = 0.2, 2014

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.117	-0.202	-0.594	-0.093	-0.371	-1.045
	(0.265)	(0.290)	(0.492)	(0.566)	(0.822)	(1.089)
Distance	-0.005	-0.003	0.020**	0.007	0.021	0.045*
	(0.006)	(0.009)	(0.009)	(0.011)	(0.018)	(0.027)
Constant	3.579		4.494		5.123	
Program FE	No	Yes	No	Yes	No	Yes
Observations	32,617	32,617	11,983	11,983	5,310	5,310
# Programs		245		220		187
R-squared	0.0001	0.0000	0.0003	0.0000	0.0003	0.0005

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A13: Distance to cutoff and Probability to change, bandwidth = 0.3, 2012

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.737***	-0.731***	0.288	0.297	0.515	0.336
	(0.210)	(0.221)	(0.467)	(0.509)	(0.748)	(0.890)
Distance	-0.010***	-0.010*	0.001	-0.000	0.018	0.015
	(0.004)	(0.005)	(0.008)	(0.009)	(0.011)	(0.019)
Constant	3.979		6.304		7.667	
Program FE	No	Yes	No	Yes	No	Yes
Observations	52,802	52,802	20,200	20,200	10,047	10,047
# Programs		312		300		278
R-squared	0.0010	0.0008	0.0000	0.0000	0.0007	0.0002

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A14: Distance to cutoff and Probability to change, bandwidth = 0.3, 2013

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.795***	-0.863***	-0.136	0.265	-0.958	-0.470
	(0.232)	(0.243)	(0.405)	(0.411)	(0.587)	(0.735)
Distance	0.003	0.003	0.009	-0.004	0.017**	0.003
	(0.005)	(0.004)	(0.006)	(0.008)	(0.008)	(0.011)
Constant	4.013		4.341		5.148	
Program FE	No	Yes	No	Yes	No	Yes
Observations	51,611	51,611	19,682	19,682	9,813	9,813
# Programs		291		270		236
R-squared	0.0003	0.0004	0.0001	0.0000	0.0003	0.0000

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A15: Distance to cutoff and Probability to change, bandwidth = 0.3, 2014

	Dep. var.: 1[Change] × 100					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.285	-0.406**	-0.461	0.041	0.510	0.787
	(0.217)	(0.199)	(0.410)	(0.472)	(0.684)	(0.880)
Distance	-0.004	-0.002	0.012**	0.002	0.010	0.020
	(0.003)	(0.003)	(0.006)	(0.006)	(0.011)	(0.015)
Constant	3.674		4.51		4.54	
Program FE	No	Yes	No	Yes	No	Yes
Observations	47,581	47,581	17,979	17,979	8,672	8,672
# Programs		249		230		208
R-squared	0.0002	0.0001	0.0002	0.0000	0.0005	0.0008

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A17: Distance to cutoff and Probability to change, bandwidth = 0.1, 2012

Dep. var.:	**1[Delete]** × **100**				**1[Extend]** × **100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.445	-0.429	-0.213	-0.317	-0.003	-0.003
	(0.324)	(0.320)	(0.253)	(0.258)	(0.005)	(0.005)
Distance	0.011	0.011	-0.010	-0.013	0.001**	0.001**
	(0.016)	(0.015)	(0.013)	(0.014)	(0.000)	(0.000)
Constant	2.989		3.055		.133	
Program FE	No	Yes	No	Yes	No	Yes
Observations	18,646	18,646	33,411	33,411	20,638	20,638
# Programs		306		311	307	307
R-squared	0.000108	0.000084	0.000123	0.000169	0.000105	0.000105

Table A18: Distance to cutoff and Probability to change, bandwidth = 0.1, 2013

Dep. var.:	**1[Delete]** × **100**				**1[Extend]** × **100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.613	-0.501	-0.259	-0.125	0.005	0.005
	(0.384)	(0.402)	(0.286)	(0.283)	(0.006)	(0.006)
Distance	0.012	-0.001	0.007	-0.009	0.000	0.000
	(0.020)	(0.028)	(0.014)	(0.019)	(0.000)	(0.000)
Constant	3.747		3.611		.117	
Program FE	No	Yes	No	Yes	No	Yes
Observations	18,691	18,691	32,681	32,681	20,449	20,449
# Programs		282		293	286	286
R-squared	0.000178	0.000159	0.000027	0.000041	0.000127	0.000127

Table A16: Distance to cutoff and Probability to change, bandwidth = 0.3, 2015

	Dep. var.: 1[Change] × **100**					
	1st Pref.		2nd Pref.		3rd Pref.	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.561***	-0.555***	-0.772**	-0.636*	-1.036**	-1.463**
	(0.176)	(0.180)	(0.331)	(0.330)	(0.483)	(0.597)
Distance	-0.002	-0.001	0.019***	0.015***	0.010	0.013
	(0.002)	(0.002)	(0.004)	(0.004)	(0.006)	(0.008)
Constant	3.464		5.044		5.323	
Program FE	No	Yes	No	Yes	No	Yes
Observations	70,042	70,042	29,801	29,801	15,973	15,973
# Programs		353		338		312
R-squared	0.0003	0.0002	0.0006	0.0002	0.0003	0.0004

Note: Table shows the regression results from Equation 1. Columns (1) and (2) show the results for changes made and signals received for the highest ranked program only. Columns (3) and (4) ((5) and (6)) show the results for the second-highest (third-highest) ranked program conditional on being below the cutoff of any higher-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A19: Distance to cutoff and Probability to change, bandwidth = 0.1, 2014

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	0.259	0.387	0.002	0.072	0.001	0.001
	(0.352)	(0.370)	(0.278)	(0.277)	(0.005)	(0.005)
Distance	-0.016	-0.029	-0.011	-0.019	0.000	0.000
	(0.018)	(0.019)	(0.014)	(0.013)	(0.000)	(0.000)
Constant	2.863		3.205		.121	
Program FE	No	Yes	No	Yes	No	Yes
Observations	17,503	17,503	29,695	29,695	19,279	19,279
# Programs		238		248	239	239
R-squared	0.000054	0.000107	0.000042	0.000053	0.000004	0.000004

Table A20: Distance to cutoff and Probability to change, bandwidth = 0.1, 2015

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.111	-0.174	-0.370*	-0.391*	0.005	0.005
	(0.260)	(0.287)	(0.194)	(0.203)	(0.005)	(0.005)
Distance	0.002	0.012	0.011	0.012	0.001***	0.001***
	(0.011)	(0.012)	(0.008)	(0.008)	(0.000)	(0.000)
Constant	2.476		2.763		.095	
Program FE	No	Yes	No	Yes	No	Yes
Observations	25,615	25,615	48,704	48,704	27,379	27,379
# Programs		344		351	346	346
R-squared	0.000009	0.000029	0.000073	0.000070	0.002418	0.002418

Table A21: Distance to cutoff and Probability to change, bandwidth = 0.2, 2012

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.209	-0.185	-0.220	-0.224	0.001	0.001
	(0.231)	(0.249)	(0.177)	(0.206)	(0.003)	(0.003)
Distance	-0.008	-0.010	-0.010**	-0.013*	0.000	0.000
	(0.006)	(0.009)	(0.005)	(0.008)	(0.000)	(0.000)
Constant	2.811		3.064		.129	
Program FE	No	Yes	No	Yes	No	Yes
Observations	36,294	36,294	67,757	67,757	40,149	40,149
# Programs		311		312	311	311
R-squared	0.000224	0.000186	0.000260	0.000269	0.000009	0.000009

Table A22: Distance to cutoff and Probability to change, bandwidth = 0.2, 2013

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.626**	-0.691**	-0.545***	-0.439**	-0.004	-0.004
	(0.281)	(0.288)	(0.203)	(0.203)	(0.004)	(0.004)
Distance	0.009	0.007	0.011**	0.004	0.000***	0.000***
	(0.008)	(0.009)	(0.005)	(0.006)	(0.000)	(0.000)
Constant	3.704		3.702		.122	
Program FE	No	Yes	No	Yes	No	Yes
Observations	35,870	35,870	66,131	66,131	39,259	39,259
# Programs		288		293	290	290
R-squared	0.000166	0.000195	0.000114	0.000082	0.000185	0.000185

Table A23: Distance to cutoff and Probability to change, bandwidth = 0.2, 2014

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	0.003	0.014	-0.230	-0.200	0.000	0.000
	(0.250)	(0.267)	(0.193)	(0.210)	(0.004)	(0.004)
Distance	-0.002	-0.002	-0.001	-0.000	0.000	0.000
	(0.006)	(0.009)	(0.004)	(0.006)	(0.000)	(0.000)
Constant	3.133		3.355		.123	
Program FE	No	Yes	No	Yes	No	Yes
Observations	32,617	32,617	59,350	59,350	35,968	35,968
# Programs		245		250	245	245
R-squared	0.000006	0.000003	0.000046	0.000026	0.000027	0.000027

Table A24: Distance to cutoff and Probability to change, bandwidth = 0.3, 2012

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.226	-0.232	-0.285**	-0.269*	-0.001	-0.001
	(0.182)	(0.182)	(0.142)	(0.152)	(0.003)	(0.003)
Distance	-0.005	-0.006	-0.006**	-0.008**	0.000	0.000
	(0.003)	(0.004)	(0.002)	(0.004)	(0.000)	(0.000)
Constant	2.775		3.116		.129	
Program FE	No	Yes	No	Yes	No	Yes
Observations	52,802	52,802	102,237	102,237	58,391	58,391
# Programs		312		313	312	312
R-squared	0.000203	0.000188	0.000264	0.000262	0.000006	0.000006

Table A25: Distance to cutoff and Probability to change, bandwidth = 0.3, 2013

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.568**	-0.639***	-0.450***	-0.326**	-0.004	-0.004
	(0.223)	(0.233)	(0.161)	(0.160)	(0.003)	(0.003)
Distance	0.004	0.003	0.003	-0.002	0.000***	0.000***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.000)	(0.000)
Constant	3.622		3.631		.121	
Program FE	No	Yes	No	Yes	No	Yes
Observations	51,611	51,611	99,720	99,720	56,497	56,497
# Programs		291		295	292	292
R-squared	0.000161	0.000197	0.000097	0.000102	0.000071	0.000071

Table A26: Distance to cutoff and Probability to change, bandwidth = 0.3, 2014

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.066	-0.117	-0.201	-0.178	-0.002	-0.002
	(0.205)	(0.198)	(0.158)	(0.176)	(0.002)	(0.002)
Distance	-0.004	-0.004	-0.002	-0.001	0.000	0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.000)	(0.000)
Constant	3.217		3.342		.125	
Program FE	No	Yes	No	Yes	No	Yes
Observations	47,581	47,581	89,744	89,744	52,491	52,491
# Programs		249		250	249	249
R-squared	0.000074	0.000053	0.000056	0.000029	0.000004	0.000004

Table A27: Distance to cutoff and Probability to change, bandwidth = 0.3, 2015

Dep. var.:	**1[Delete] × 100**				**1[Extend] × 100**	
	1st Pref.		any Pref.		ROL	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.173	-0.200	-0.417***	-0.419***	-0.001	-0.001
	(0.157)	(0.159)	(0.114)	(0.111)	(0.003)	(0.003)
Distance	-0.000	0.001	0.001	0.002	0.000***	0.000***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)
Constant	2.592		2.857		.099	
Program FE	No	Yes	No	Yes	No	Yes
Observations	70,042	70,042	147,730	147,730	75,005	75,005
# Programs		353		355	353	353
R-squared	0.000035	0.000023	0.000117	0.000094	0.001463	0.001463

A.3.5 Robustness checks

Table A28: Distance to cutoff and Probability to change, bandwidth = 0.1, 2012

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.938**	-0.612	-0.473	-0.274	-0.473	-0.707
	(0.475)	(0.521)	(0.580)	(0.651)	(0.580)	(0.612)
Distance	0.005	-0.006	-0.008	-0.007	-0.008	0.010
	(0.024)	(0.025)	(0.026)	(0.037)	(0.026)	(0.037)
Female					0.601	0.544
					(0.504)	(0.548)
Above × Female					-0.465	0.058
					(0.750)	(0.855)
Female × Dist					0.013	-0.010
					(0.035)	(0.042)
Constant	4.288		3.686		3.686	
Program FE	No	Yes	No	Yes	No	Yes
Observations	11,497	11,497	7,149	7,149	18,646	18,646
# Programs		274		239		306
R-squared	0.0005	0.0002	0.0003	0.0001	0.0005	0.0004

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A29: Distance to cutoff and Probability to change, bandwidth = 0.1, 2013

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.924*	-1.456**	-1.065	-1.475**	-1.065	-0.751
	(0.505)	(0.592)	(0.650)	(0.572)	(0.650)	(0.549)
Distance	0.012	0.025	0.016	0.032	0.016	0.003
	(0.027)	(0.039)	(0.033)	(0.031)	(0.033)	(0.031)
Female					-0.371	0.175
					(0.547)	(0.545)
Above × Female					0.142	-0.180
					(0.823)	(0.762)
Female × Dist					-0.005	-0.001
					(0.043)	(0.041)
Constant	4.066		4.437		4.437	
Program FE	No	Yes	No	Yes	No	Yes
Observations	11,068	11,068	7,623	7,623	18,691	18,691
# Programs		247		205		282
R-squared	0.0005	0.0008	0.0005	0.0006	0.0005	0.0004

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A30: Distance to cutoff and Probability to change, bandwidth = 0.1, 2014

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	0.165	0.504	0.284	0.411	0.284	0.057
	(0.482)	(0.553)	(0.578)	(0.601)	(0.578)	(0.582)
Distance	-0.023	-0.063***	-0.027	-0.018	-0.027	-0.026
	(0.024)	(0.021)	(0.030)	(0.034)	(0.030)	(0.034)
Female					0.387	0.144
					(0.481)	(0.526)
Above × Female					-0.118	0.287
					(0.752)	(0.796)
Female × Dist					0.004	-0.017
					(0.038)	(0.036)
Constant	3.488		3.101		3.101	
Program FE	No	Yes	No	Yes	No	Yes
Observations	10,597	10,597	6,906	6,906	17,503	17,503
# Programs		207		189		238
R-squared	0.0001	0.0004	0.0001	0.0001	0.0002	0.0002

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A31: Distance to cutoff and Probability to change, bandwidth = 0.1, 2015

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.402	-0.328	-0.502	-0.375	-0.502	-0.354
	(0.383)	(0.452)	(0.456)	(0.450)	(0.456)	(0.425)
Distance	-0.002	-0.001	0.001	-0.003	0.001	0.005
	(0.018)	(0.020)	(0.019)	(0.017)	(0.019)	(0.016)
Female					0.163	0.368
					(0.395)	(0.394)
Above × Female					0.100	0.050
					(0.595)	(0.582)
Female × Dist					-0.004	-0.009
					(0.026)	(0.019)
Constant	3.349		3.186		3.186	
Program FE	No	Yes	No	Yes	No	Yes
Observations	15,774	15,774	9,841	9,841	25,615	25,615
# Programs		307		267		344
R-squared	0.0001	0.0001	0.0002	0.0001	0.0002	0.0002

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A32: Distance to cutoff and Probability to change, bandwidth = 0.2, 2012

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.703**	-0.606*	-0.420	-0.629	-0.420	-0.471
	(0.343)	(0.352)	(0.419)	(0.498)	(0.419)	(0.462)
Distance	-0.013	-0.017**	-0.022*	-0.013	-0.022*	-0.021
	(0.009)	(0.008)	(0.012)	(0.020)	(0.012)	(0.017)
Female					0.398	0.512
					(0.353)	(0.341)
Above × Female					-0.283	-0.085
					(0.542)	(0.538)
Female × Dist					0.009	0.006
					(0.015)	(0.014)
Constant	4.151		3.753		3.753	
Program FE	No	Yes	No	Yes	No	Yes
Observations	22,172	22,172	14,122	14,122	36,294	36,294
# Programs		291		267		311
R-squared	0.0008	0.0007	0.0010	0.0005	0.0010	0.0007

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A33: Distance to cutoff and Probability to change, bandwidth = 0.2, 2013

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.665*	-0.872**	-1.217***	-1.381***	-1.217***	-1.208***
	(0.378)	(0.428)	(0.461)	(0.423)	(0.461)	(0.414)
Distance	0.001	0.002	0.018	0.019	0.018	0.017
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)
Female					-0.480	-0.165
					(0.391)	(0.370)
Above × Female					0.553	0.454
					(0.597)	(0.592)
Female × Dist					-0.017	-0.018
					(0.017)	(0.018)
Constant	3.921		4.401		4.401	
Program FE	No	Yes	No	Yes	No	Yes
Observations	21,204	21,204	14,666	14,666	35,870	35,870
# Programs		263		234		288
R-squared	0.0003	0.0004	0.0005	0.0006	0.0004	0.0004

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A34: Distance to cutoff and Probability to change, bandwidth = 0.2, 2014

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.182	-0.330	0.001	-0.077	0.001	-0.093
	(0.338)	(0.375)	(0.426)	(0.422)	(0.426)	(0.397)
Distance	-0.008	-0.009	-0.002	0.005	-0.002	0.001
	(0.008)	(0.009)	(0.011)	(0.012)	(0.011)	(0.011)
Female					0.148	0.147
					(0.351)	(0.321)
Above × Female					-0.183	-0.157
					(0.544)	(0.510)
Female × Dist					-0.006	-0.007
					(0.013)	(0.010)
Constant	3.629		3.481		3.481	
Program FE	No	Yes	No	Yes	No	Yes
Observations	19,429	19,429	13,188	13,188	32,617	32,617
# Programs		224		210		245
R-squared	0.0002	0.0002	0.0000	0.0000	0.0001	0.0001

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A35: Distance to cutoff and Probability to change, bandwidth = 0.3, 2012

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.806***	-0.818***	-0.626*	-0.905**	-0.626*	-0.709**
	(0.270)	(0.289)	(0.336)	(0.352)	(0.336)	(0.331)
Distance	-0.011***	-0.015***	-0.009	-0.002	-0.009	-0.007
	(0.004)	(0.005)	(0.006)	(0.008)	(0.006)	(0.007)
Female					0.260	0.418
					(0.286)	(0.295)
Above × Female					-0.180	-0.051
					(0.431)	(0.418)
Female × Dist					-0.003	-0.005
					(0.008)	(0.005)
Constant	4.076		3.817		3.817	
Program FE	No	Yes	No	Yes	No	Yes
Observations	31,929	31,929	20,873	20,873	52,802	52,802
# Programs		295		274		312
R-squared	0.0012	0.0012	0.0007	0.0006	0.0011	0.0009

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A36: Distance to cutoff and Probability to change, bandwidth = 0.3, 2013

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.696**	-0.850**	-0.927**	-1.052***	-0.927**	-1.004***
	(0.306)	(0.344)	(0.363)	(0.367)	(0.363)	(0.352)
Distance	0.001	0.002	0.005	0.005	0.005	0.006
	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Female					-0.253	-0.020
					(0.313)	(0.296)
Above × Female					0.231	0.252
					(0.474)	(0.467)
Female × Dist					-0.004	-0.006
					(0.009)	(0.009)
Constant	3.906		4.158		4.158	
Program FE	No	Yes	No	Yes	No	Yes
Observations	30,308	30,308	21,303	21,303	51,611	51,611
# Programs		271		252		291
R-squared	0.0003	0.0004	0.0004	0.0005	0.0004	0.0004

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A37: Distance to cutoff and Probability to change, bandwidth = 0.3, 2014

	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.285	-0.398	-0.281	-0.307	-0.281	-0.468
	(0.277)	(0.273)	(0.351)	(0.325)	(0.351)	(0.303)
Distance	-0.004	-0.003	-0.004	-0.000	-0.004	-0.002
	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)	(0.004)
Female					0.029	0.004
					(0.292)	(0.247)
Above × Female					-0.004	0.099
					(0.447)	(0.398)
Female × Dist					0.000	0.000
					(0.007)	(0.004)
Constant	3.685		3.655		3.655	
Program FE	No	Yes	No	Yes	No	Yes
Observations	28,425	28,425	19,156	19,156	47,581	47,581
# Programs		233		224		249
R-squared	0.0002	0.0002	0.0002	0.0001	0.0002	0.0001

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

Table A38: Distance to cutoff and Probability to change, bandwidth = 0.3, 2015

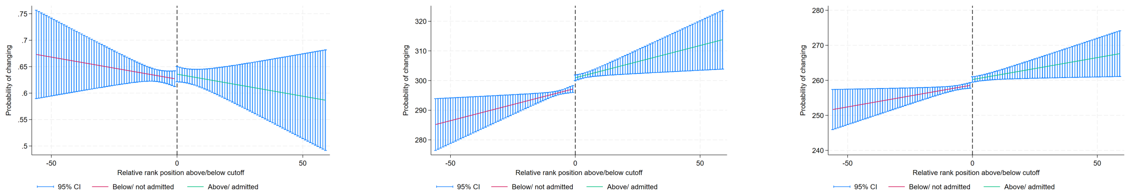
	Dep. var.: 1[Change] × 100					
	Female		Male		Jointly	
	(1)	(2)	(3)	(4)	(5)	(6)
Above	-0.621***	-0.558**	-0.450	-0.433	-0.450	-0.426
	(0.227)	(0.244)	(0.280)	(0.285)	(0.280)	(0.274)
Distance	-0.002	-0.004	-0.002	0.001	-0.002	-0.001
	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Female					0.294	0.290
					(0.233)	(0.233)
Above × Female					-0.172	-0.212
					(0.360)	(0.368)
Female × Dist					-0.000	-0.001
					(0.005)	(0.007)
Constant	3.576		3.281		3.281	
Program FE	No	Yes	No	Yes	No	Yes
Observations	42,082	42,082	27,960	27,960	70,042	70,042
# Programs		336		316		353
R-squared	0.0004	0.0003	0.0002	0.0001	0.0004	0.0003

Note: Table shows the regression results from Equation 1 with alternative dependent variables. Columns (1) and (2) show the results for the probability to delete the highest-ranked program, Columns (3) and (4) for the probability to delete any ranked program and Columns (5) and (6) for the probability to extend the ROL when receiving a signal on admission probability for the highest-ranked program. Robust standard errors in parentheses. * p-value < .1, ** p-value < .05, *** p-value < .01.

A.3.6 No discontinuity

Figure A8: No discontinuity in counterfactuals, bw = 10%, 2012

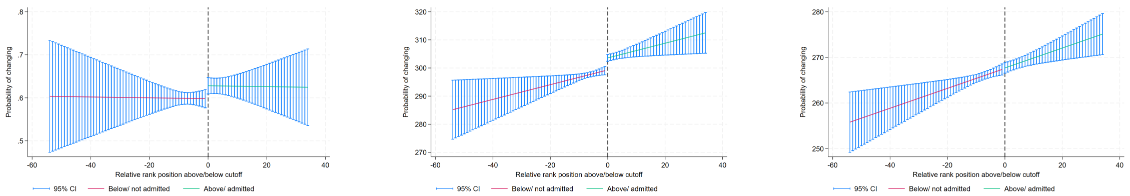
(a) Share female (b) Weighted State Exam Grades (c) Weighted High School Grades



Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A9: No discontinuity in counterfactuals, bw = 10%, 2013

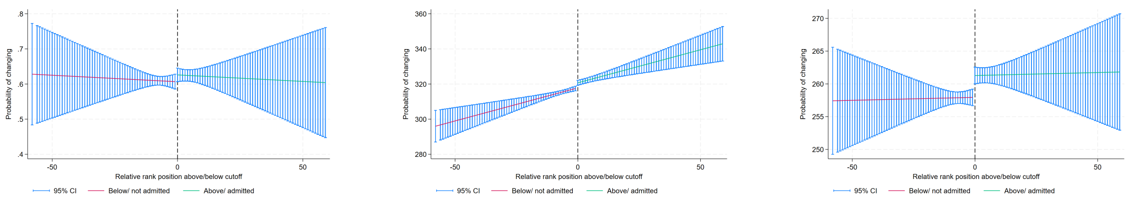
(a) Share female (b) Weighted State Exam Grades (c) Weighted High School Grades



Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A10: No discontinuity in counterfactuals, bw = 10%, 2014

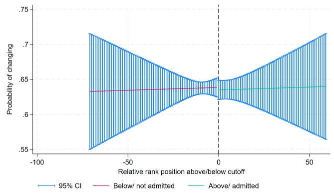
(a) Share female (b) Weighted State Exam Grades (c) Weighted High School Grades



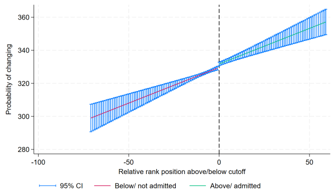
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A11: No discontinuity in counterfactuals, bw = 10%, 2015

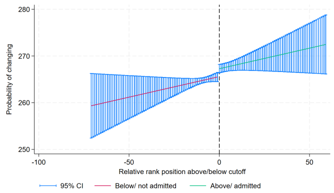
(a) Share female



(b) Weighted State Exam Grades



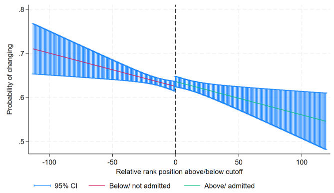
(c) Weighted High School Grades



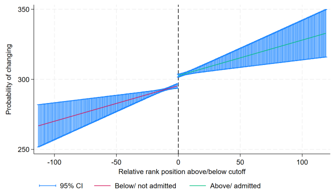
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A12: No discontinuity in counterfactuals, bw = 20%, 2012

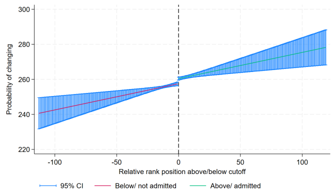
(a) Share female



(b) Weighted State Exam Grades



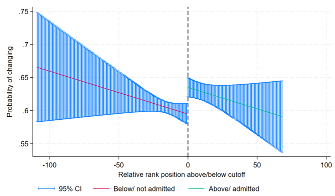
(c) Weighted High School Grades



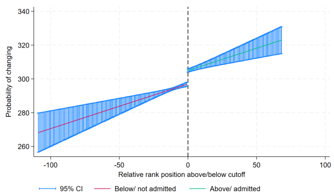
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A13: No discontinuity in counterfactuals, bw = 20%, 2013

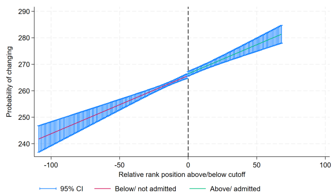
(a) Share female



(b) Weighted State Exam Grades



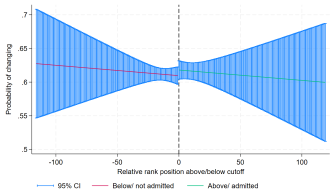
(c) Weighted High School Grades



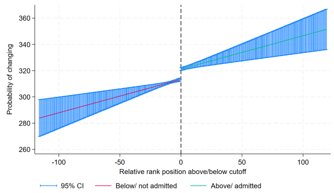
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A14: No discontinuity in counterfactuals, bw = 20%, 2014

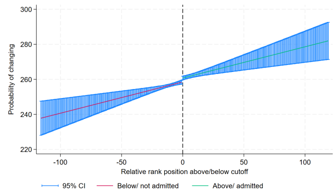
(a) Share female



(b) Weighted State Exam Grades



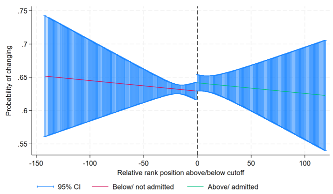
(c) Weighted High School Grades



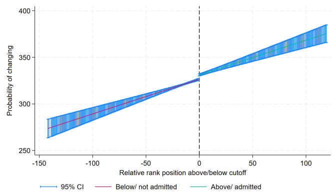
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A15: No discontinuity in counterfactuals, bw = 20%, 2015

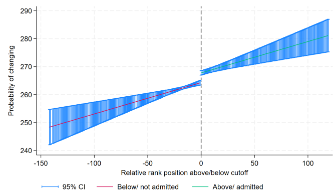
(a) Share female



(b) Weighted State Exam Grades



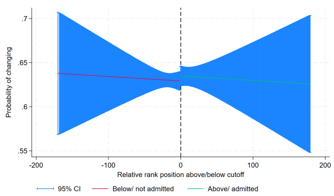
(c) Weighted High School Grades



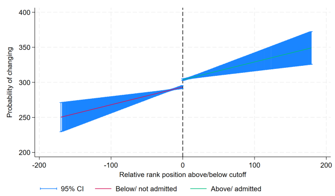
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A16: No discontinuity in counterfactuals, bw = 30%, 2012

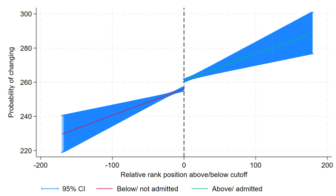
(a) Share female



(b) Weighted State Exam Grades



(c) Weighted High School Grades



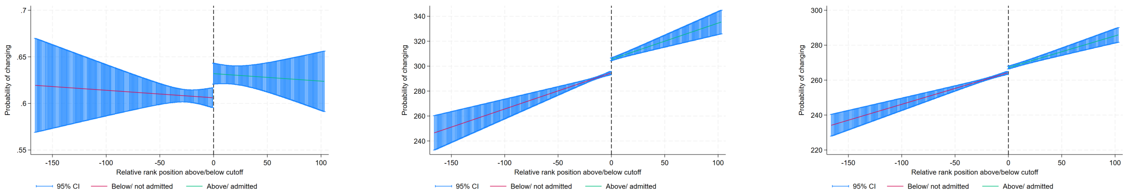
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A17: No discontinuity in counterfactuals, bw = 30%, 2013

(a) Share female

(b) Weighted State Exam Grades

(c) Weighted High School Grades



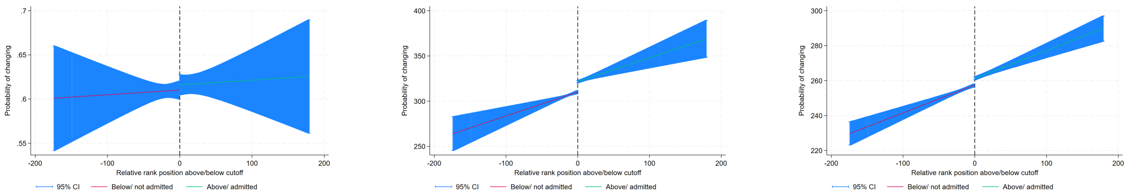
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A18: No discontinuity in counterfactuals, bw = 30%, 2014

(a) Share female

(b) Weighted State Exam Grades

(c) Weighted High School Grades



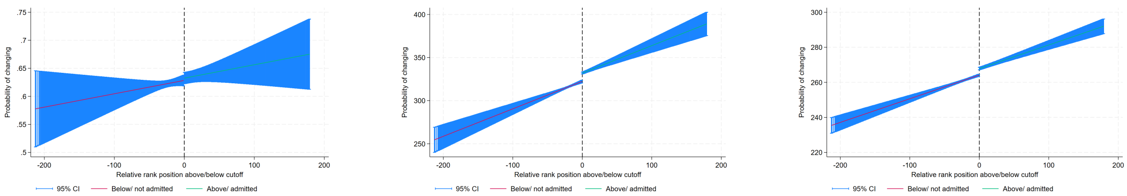
Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

Figure A19: No discontinuity in counterfactuals, bw = 30%, 2015

(a) Share female

(b) Weighted State Exam Grades

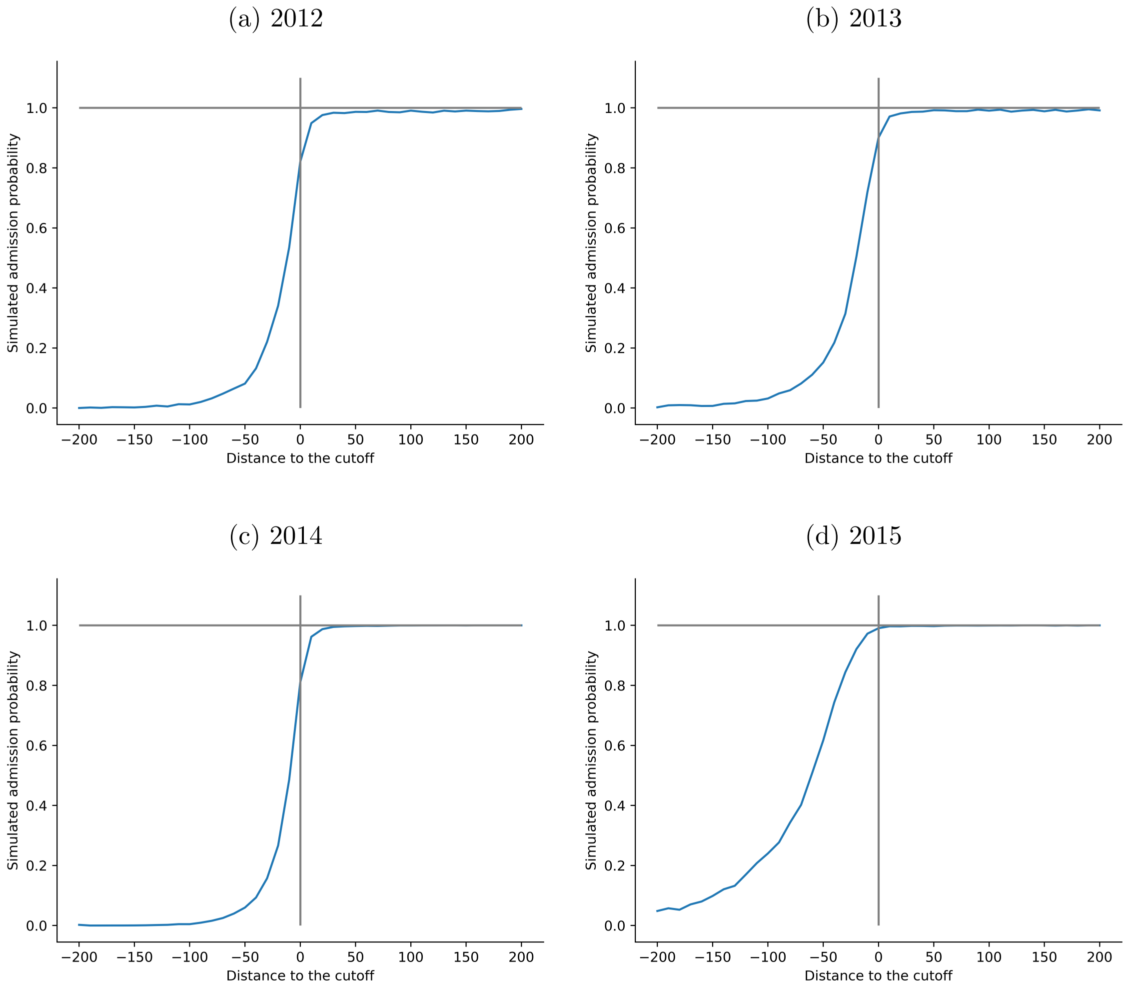
(c) Weighted High School Grades



Note: In these figures we explore discontinuities in counterfactuals. In Panel a), the dependent variable is the share of women, in Panel b) it is weighted state exam grades and in Panel c) it is weighted high school grades. The blue vertical lines show the 95% confidence bands.

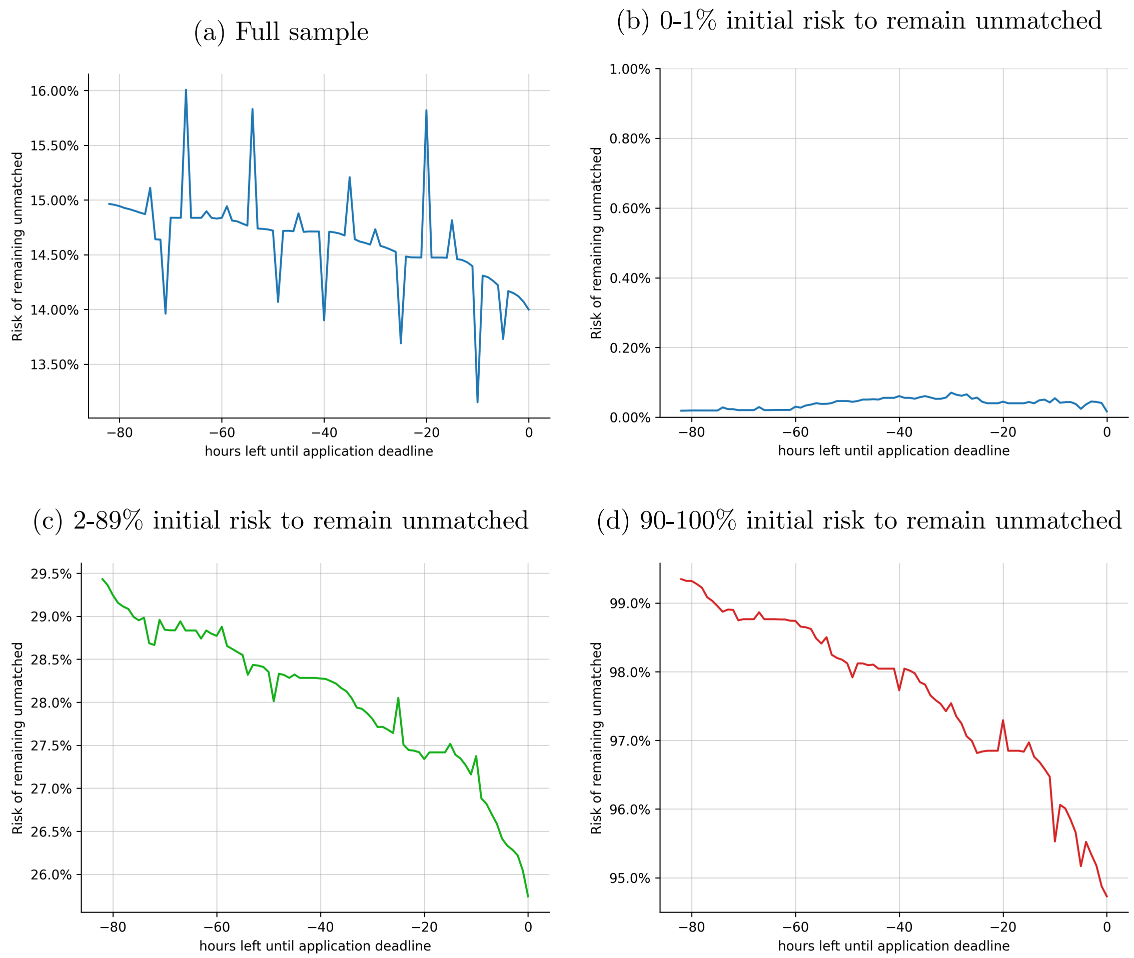
A.4 Developing a strategy

Figure A20: Simulated admission probability around the admission cutoff



Note: Figures show the simulated admission probability by the rank distance around the final admission cutoff.

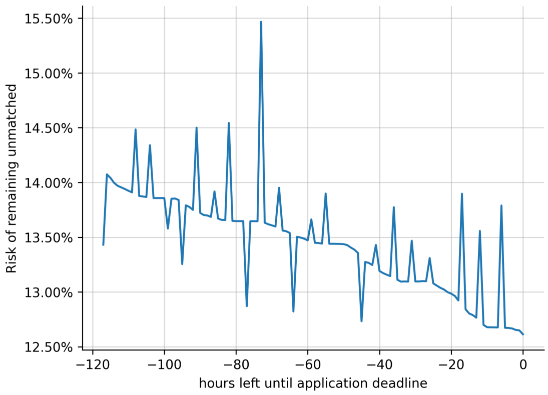
Figure A21: Average risk to remain unmatched over time, by initial risk (2012)



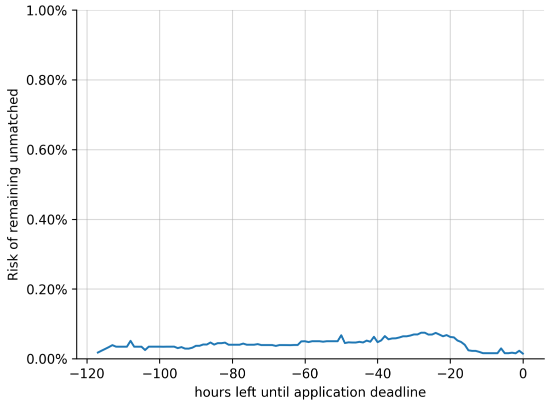
Note: Figure shows how the average risk to remain unmatched evolves over time for two subgroups. In Panel a) we show the average risk for the group with an initial risk to remain unmatched of 0-1%, in Panel b) we show the same for the group with a high initial risk of 90-100%. The group with an initial risk of 0-1% makes up 77.2%, the group with an initial risk of 1-89% makes up 11.1% and the group with an initial risk of 90-100% makes up 11.8%.

Figure A22: Average risk to remain unmatched over time, by initial risk (2013)

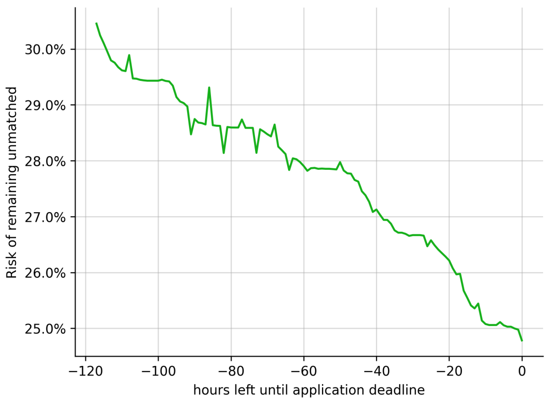
(a) Full sample



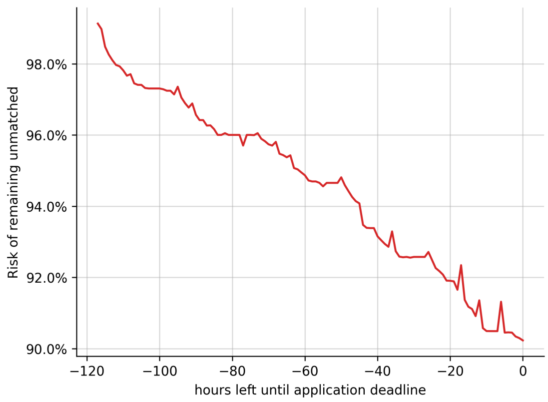
(b) 0-1% initial risk to remain unmatched



(c) 2-89% initial risk to remain unmatched



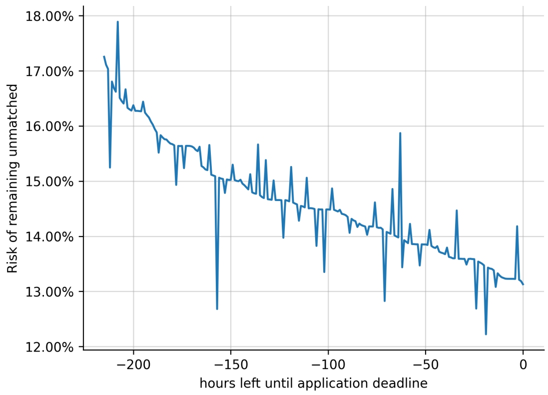
(d) 90-100% initial risk to remain unmatched



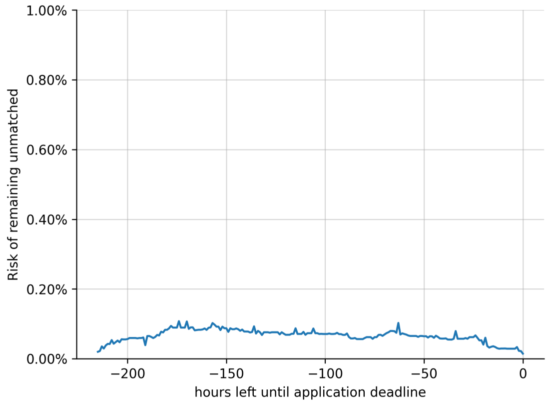
Note: Figure shows how the average risk to remain unmatched evolves over time for two subgroups. In Panel a) we show the average risk for the group with an initial risk to remain unmatched of 0-1%, in Panel b) we show the same for the group with a high initial risk of 90-100%. The group with an initial risk of 0-1% makes up 78.8%, the group with an initial risk of 1-89% makes up 11% and the group with an initial risk of 90-100% makes up 10.2%.

Figure A23: Average risk to remain unmatched over time, by initial risk (2014)

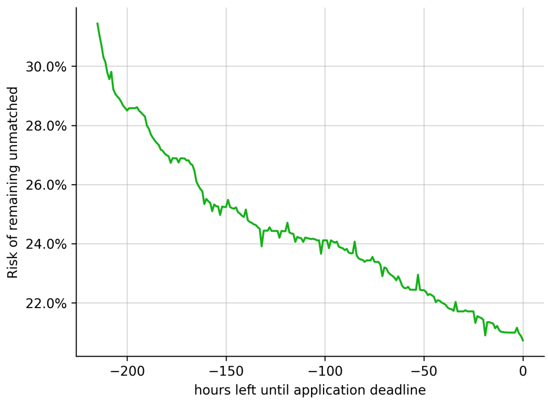
(a) Full sample



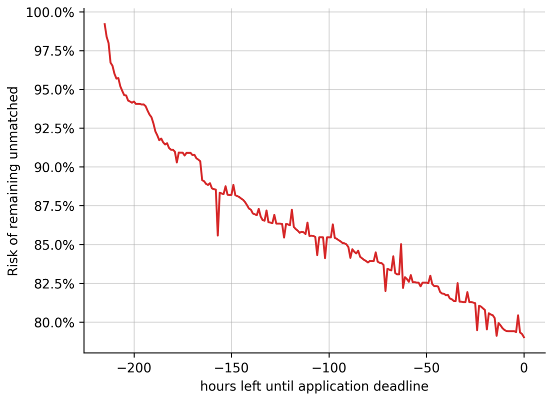
(b) 0-1% initial risk to remain unmatched



(c) 2-89% initial risk to remain unmatched



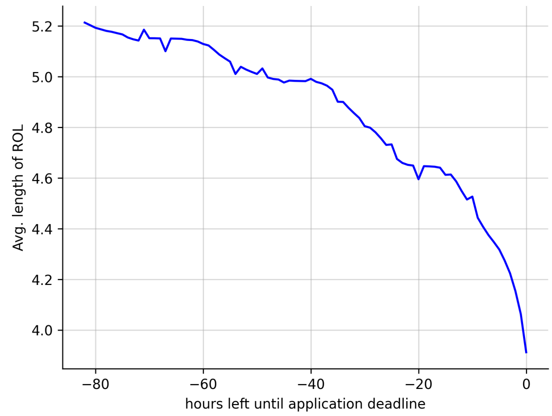
(d) 90-100% initial risk to remain unmatched



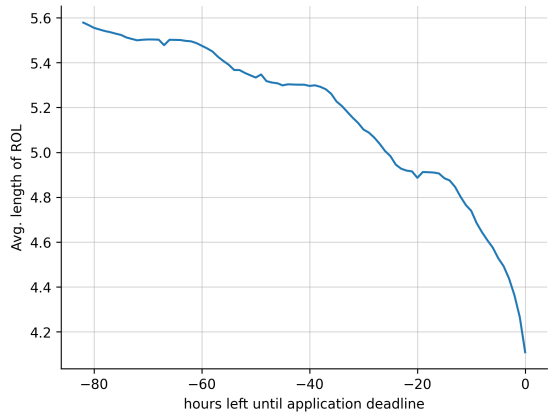
Note: Figure shows how the average risk to remain unmatched evolves over time for two subgroups. In Panel a) we show the average risk for the group with an initial risk to remain unmatched of 0-1%, in Panel b) we show the same for the group with a high initial risk of 90-100%. The group with an initial risk of 0-1% makes up 73.6%, the group with an initial risk of 1-89% makes up 13.2% and the group with an initial risk of 90-100% makes up 13.2%.

Figure A24: Average number of ranked programs over time, by initial risk (2012)

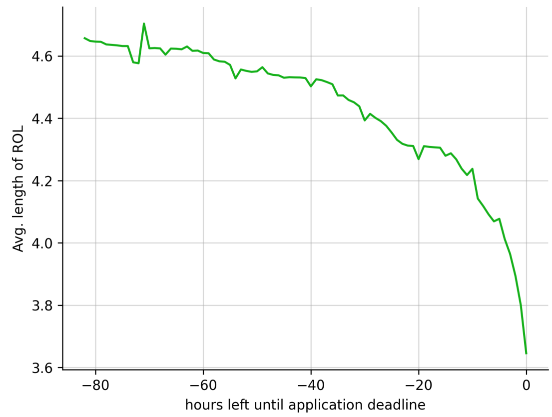
(a) Full sample



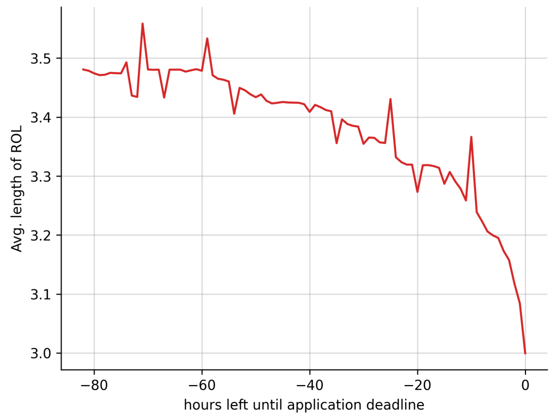
(b) 0-1% initial risk to remain unmatched



(c) 2-89% initial risk to remain unmatched



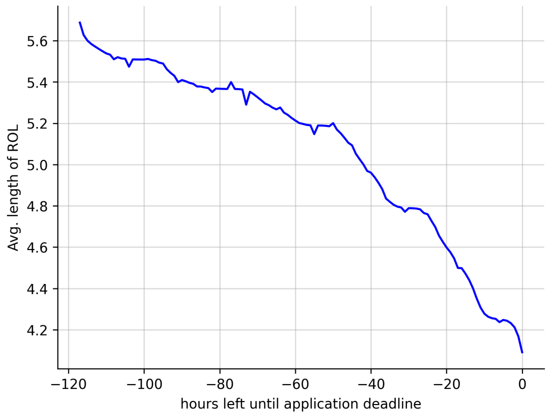
(d) 90-100% initial risk to remain unmatched



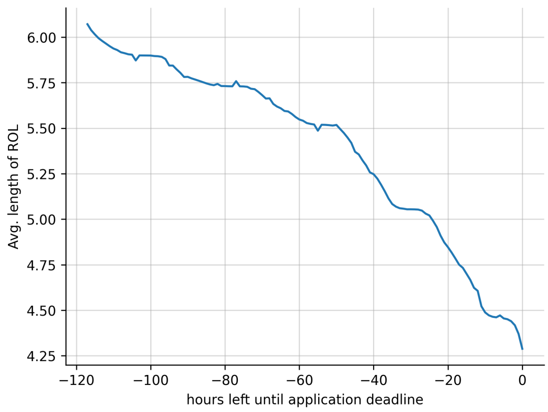
Note: Figure shows how the average number of ranked programs evolves over time for two subgroups. In Panel a) we show the average length of the ROL for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 77.2%, the group with an initial risk of 1-89% makes up 11.1% and the group with an initial risk of 90-100% makes up 11.8%.

Figure A25: Average number of ranked programs over time, by initial risk (2013)

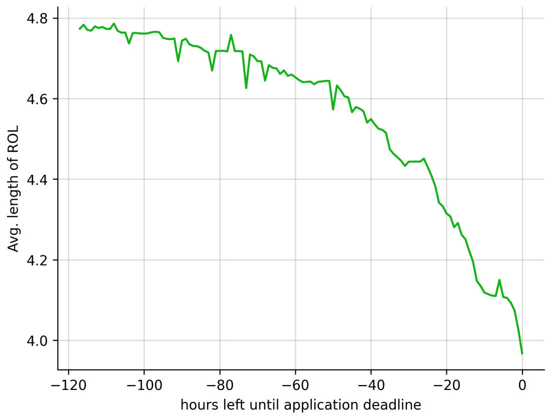
(a) Full sample



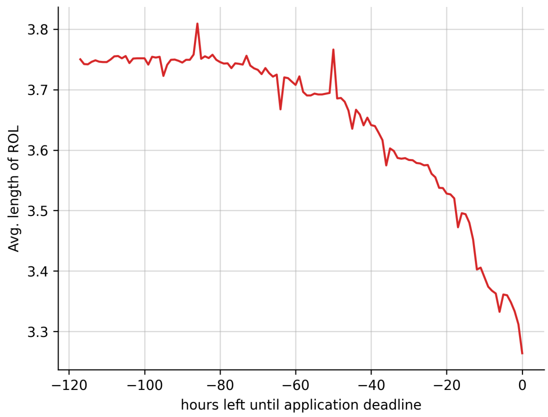
(b) 0-1% initial risk to remain unmatched



(c) 2-89% initial risk to remain unmatched



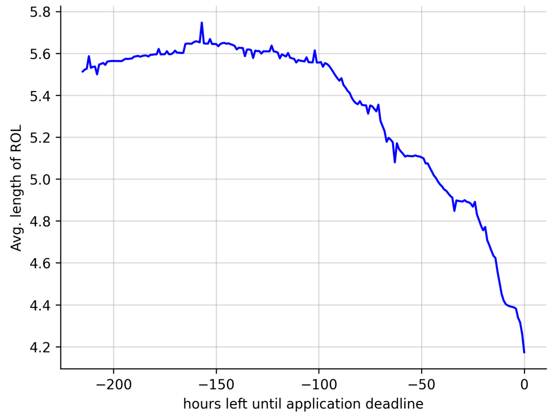
(d) 90-100% initial risk to remain unmatched



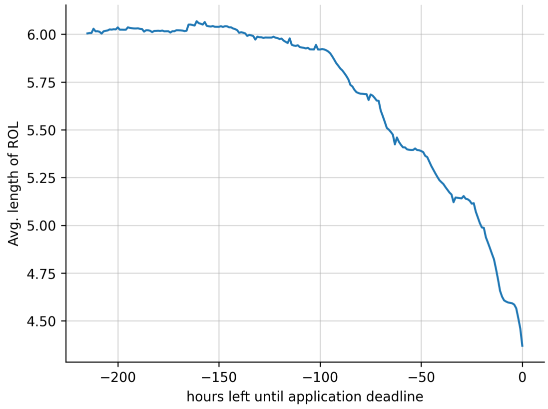
Note: Figure shows how the average number of ranked programs evolves over time for two subgroups. In Panel a) we show the average length of the ROL for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 78.8%, the group with an initial risk of 1-89% makes up 11% and the group with an initial risk of 90-100% makes up 10.2%.

Figure A26: Average number of ranked programs over time, by initial risk (2014)

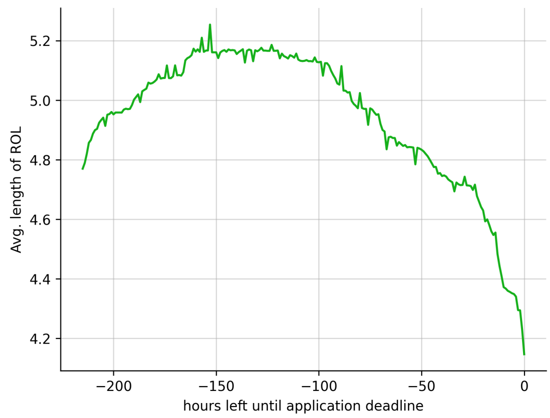
(a) Full sample



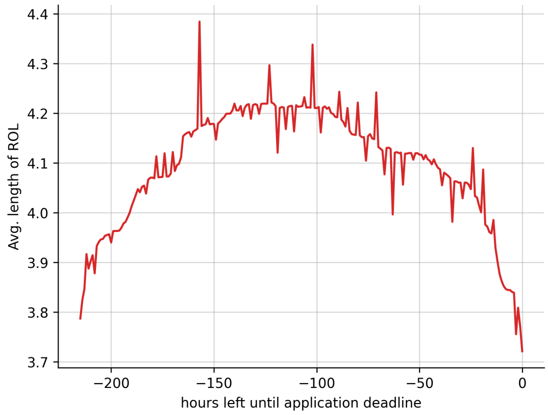
(b) 0-1% initial risk to remain unmatched



(c) 2-89% initial risk to remain unmatched

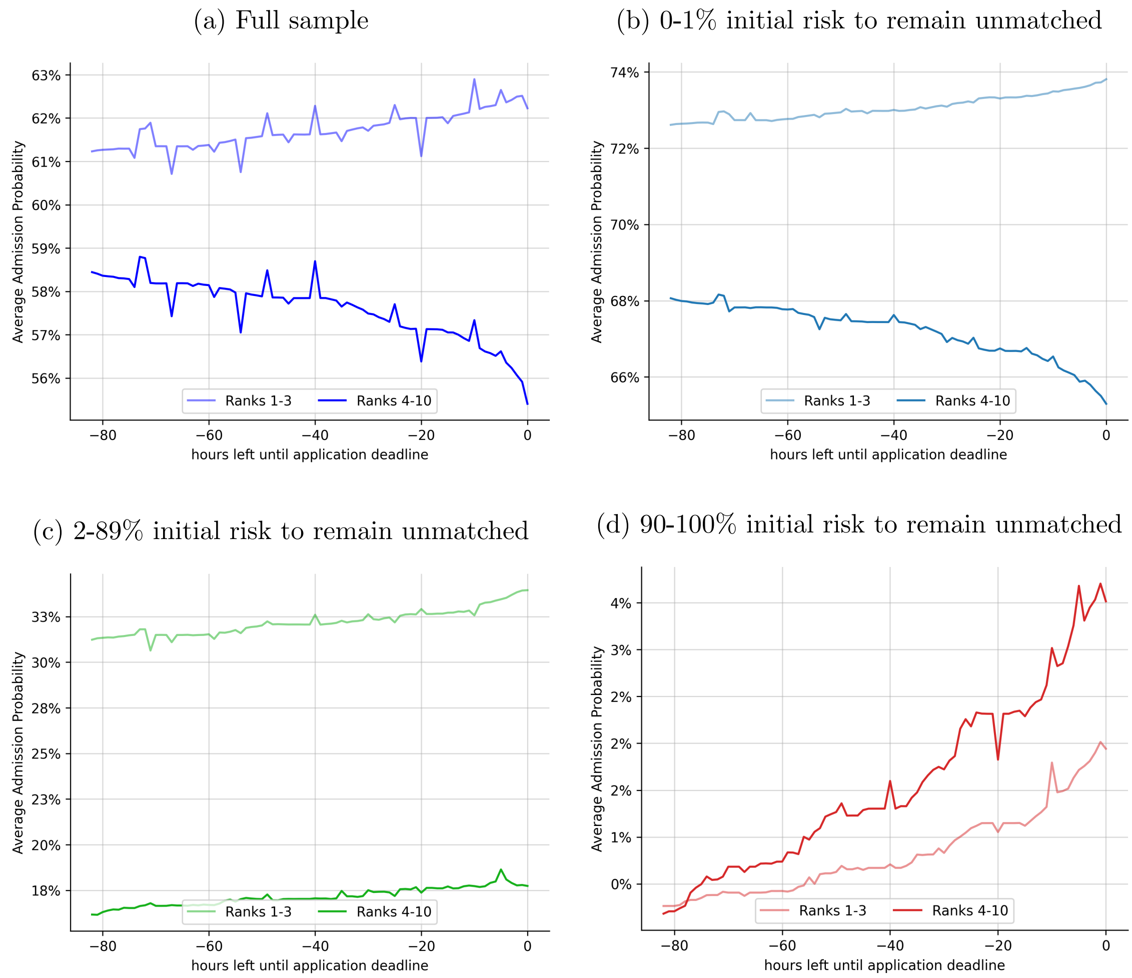


(d) 90-100% initial risk to remain unmatched



Note: Figure shows how the average number of ranked programs evolves over time for two subgroups. In Panel a) we show the average length of the ROL for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 73.6%, the group with an initial risk of 1-89% makes up 13.2% and the group with an initial risk of 90-100% makes up 13.2%.

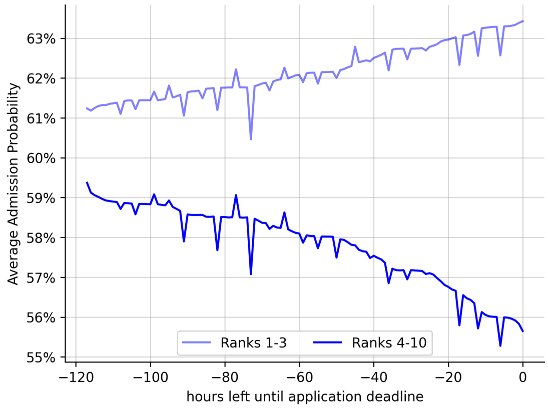
Figure A27: Average risk to remain unmatched over time, by initial risk (2012)



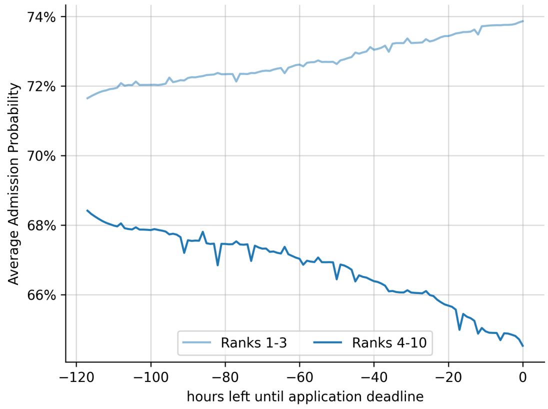
Note: Figure shows how the average admission probability of the three highest-ranked programs and of all lower-ranked programs evolves over time for two subgroups. In Panel a) we show the average admission probability for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 77.2%, the group with an initial risk of 1-89% makes up 11.1% and the group with an initial risk of 90-100% makes up 11.8%.

Figure A28: Average risk to remain unmatched over time, by initial risk (2013)

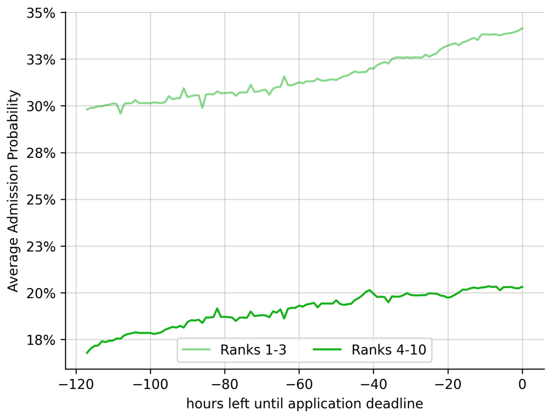
(a) Full sample



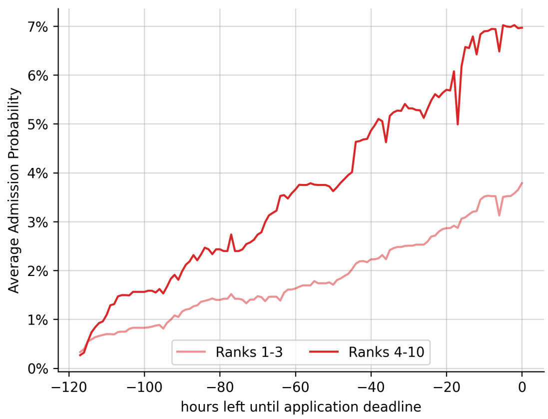
(b) 0-1% initial risk to remain unmatched



(c) 2-89% initial risk to remain unmatched

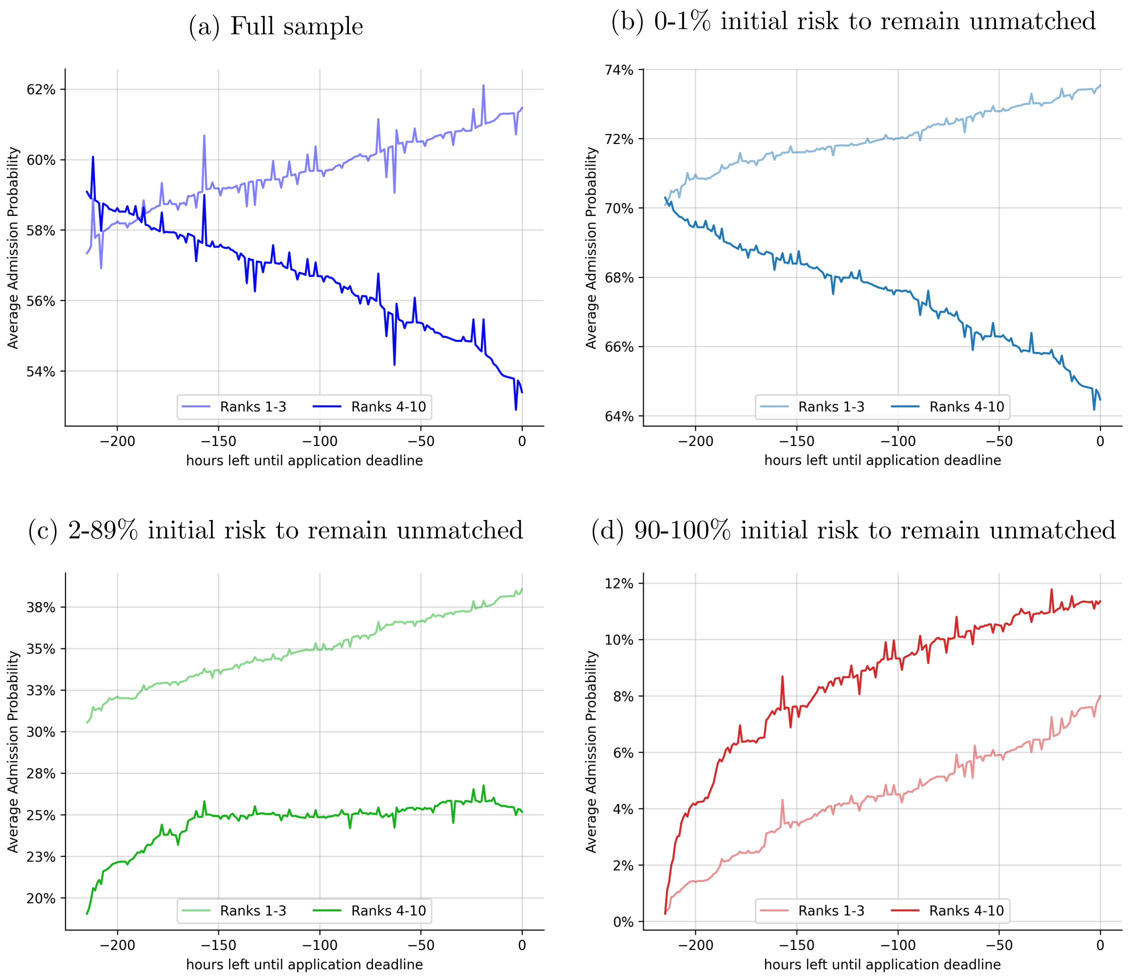


(d) 90-100% initial risk to remain unmatched



Note: Figure shows how the average admission probability of the three highest-ranked programs and of all lower-ranked programs evolves over time for two subgroups. In Panel a) we show the average admission probability for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 78.8%, the group with an initial risk of 1-89% makes up 11% and the group with an initial risk of 90-100% makes up 10.2%.

Figure A29: Average risk to remain unmatched over time, by initial risk (2014)



Note: Figure shows how the average admission probability of the three highest-ranked programs and of all lower-ranked programs evolves over time for two subgroups. In Panel a) we show the average admission probability for the full sample, in Panel b), c) and d) for the subgroup of applicants with initial risks to remain unmatched of 0-1%, 2-89% and 90-100% respectively. The group with an initial risk of 0-1% makes up 73.6%, the group with an initial risk of 1-89% makes up 13.2% and the group with an initial risk of 90-100% makes up 13.2%.

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