Cognitive Distortions in Complex Decisions: Evidence from Centralized College Admission

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[Preliminary Draft; Latest Version Here] §

Abstract

Constructing optimal rank-order lists in centralized matching systems often entails sophisticated risk-taking consideration. We empirically study an admission system that employs a constrained Deferred Acceptance Algorithm to understand how students construct their lists. Students appear overly cautious with their top choices and most of them do not always put safer choices at a lower-ranked spot on the list. We propose that the Model of Directed Cognition could explain such choices. Applicants using the model myopically focus on the spot they are contemplating and neglect its impact on the rest of the list. To differentiate from alternative hypotheses, we deploy an in-field experiment that pinpoints a core prediction of our model concerning framing effects and find clear evidence of it. Structural estimation suggests that 45%∼55% of the sample are better described by our model and that this boundedly rational decision rule explains 83% of outcome inequality across socioeconomic groups.

Keywords: Cognition, Complexity, Risk-Taking, Centralized Admission
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1 Introduction

Centralized admission systems play an important role in student-to-school matching around the world. In these systems, students are assigned to schools based on the outcome of a matching mechanism that accounts for students' reported preferences (typically called rank-order lists, or ROLs) and their priority scores. In most real-world mechanisms, determining the optimal ROL requires significant sophistication on the part of the student. It consists of multiple risk-reward tradeoff problems that require backward induction, contingent reasoning, and aggregating risk across choices, which applicants may have trouble grasping.[1] Failure to grasp the optimal strategy results in undesirable outcomes at later stages of education, which could ultimately influence career choice and economic mobility.[2]

We empirically investigate the consequences of sub-optimal application choices among college applicants in Ningxia, China. The centralized admission system in Ningxia employs a constrained Deferred Acceptance Algorithm[3] where eligible students can list up to four colleges from 239 first-tier colleges. The algorithm works by considering students' demand in order of their scores from the College Entrance Exam (CEE). When the algorithm reaches a given student, it considers the student's first-choice college and assigns the student to this choice if the admission quota of the college has not been filled. The algorithm checks the next choice only when the choice in question has already been filled by higher-scoring students, and repeats this process until the fourth choice. In practice, the student is relegated to a second-tier college outside of the 239 choices if all of the listed colleges have been filled.

Undoubtedly, any student needs to manage the risk of relegation to a second-tier college by listing at least one safe first-tier college on her ROL. The amount of risk that the student should take for the other three choices, however, is less obvious. Intuitively, the cost of not getting into one's first-choice college is less devastating than not getting into one's fourth choice - if the first choice is missed, the student can just move on to the next choice without worrying about a looming relegation. The optimal choice for any spot depends on the consequences of rejection, and the consequences of rejection depend on the schools listed

[1] Chade and Smith (2006) and Shorrer (2019) theoretically characterize and develop algorithms for constructing the optimal portfolio in stylized settings of college admission, both of which invoke dynamic programming thinking that is similar to the logic of backward induction. Calsamiglia et al. (2020) show that backward induction solves computationally intractable problems for a wide class of mechanisms that are used in real college admission systems. Camerer et al. (1993) and Johnson et al. (2002) document failure of backward induction in extensive form games. Esponda and Vespa (2016) and Martínez-Marquina et al. (2019) document how uncertainty impedes contingent reasoning. Rabin and Weizsäcker (2009) document decision makers' general tendency to evaluate risk in isolation.

[2] Impacts of postsecondary education on labor market income have been documented in many countries, including Chile (Hastings et al., 2013), China (Jia and Li, 2016), and the US (Chetty et al., 2020).

[3] As detailed in Section 2.2, this is also a serial dictatorship mechanism.

lower on the ROL. This intuition prescribes, that rather than viewing each spot in isolation, the student should formulate a contingency plan to make the most of the entire portfolio by backward induction.

We obtained access to the administrative data on students' application lists. We find that, even with their first choices, 25% of the students choose a safe college – i.e., one whose probability of vacancy availability is larger than 84.3% when the system processes their requests[4], suggesting that many students are not very selective in their first choices. Meanwhile, 61.5% of the students exhibit "competitiveness reversals", defined as ranking a less-selective college above a more-selective college on their ROLs, resembling evidence from many other contexts (Lucas and Mbiti, 2012; Ajayi, 2013; He, 2015; Rees-Jones et al., 2020; Larroucau et al., 2021).

These behaviors correlate with demographics and contribute to inequality in admission outcomes. Students coming from disadvantaged areas are substantially more cautious in their first choices and are more likely to exhibit competitiveness reversals on their ROL. Conditional on priority scores, the most disadvantaged students on average end up in colleges whose selectivity, as measured by mean of cutoffs during 2014-2018, are 0.13 standard deviation lower than the most advantaged students.

To explain these empirical patterns, we propose that a boundedly rational decision rule, inspired by the Directed Cognition Model (henceforth the DC Model) (Gabaix et al., 2006), can naturally fit these patterns. In our context, the DC Model predicts that students focus their cognition entirely on the single spot they are contemplating (i.e., they choose a college to maximize improvement of expected utility for a portfolio that consists of that spot and a subjective, perhaps psychological, outside option) and ignore the impact of this choice on the rest of the ROL. This decision rule reduces a portfolio choice problem to repeated discrete choice problems, dispensing with backward induction, contingent reasoning, or the difficulty of aggregating risk across choices.

Because most centralized mechanisms share the feature that optimal choices across different spots are interdependent, our hypothesis, if substantiated, could provide a descriptive model of suboptimal strategic behavior, and have general implications for the design of matching systems. However, testing decision optimality is difficult for this type of problem because applicants may have heterogeneous preferences (Agarwal and Somaini, 2018, 2019). This may be the reason that limited progress has been made on understanding whether decision-makers respond to such interdependency in a systematically suboptimal way[5]. We

[4]This probability is sometimes refer to as the unconditional probability, i.e. the probability of being admitted in the absence of the higher-ranked choices. It is also the probability of meeting the admission cutoff of a college.

[5]Significant progress has been made in understanding mistakes in the absence of strategic concerns and

are able to perform this task with the help of an incentivized survey experiment, conducted among a subset of student applicants right after they have submitted ROLs. Additionally, when analyzing ROLs in the administrative data, the variations in assignment probability across individual students enable us to differentiate our hypothesis from various types of preference heterogeneity. To understand how the DC Model can be differentiated from alternative hypotheses with the help of the aforementioned data, we briefly discuss the four main predictions of the DC Model as well as their empirical support.

Our first prediction, labeled **"Top-Choice Cautiousness"**, says that, compared to the Rational Rule, the DC Model takes substantially less risk for their first choices. However, their fourth choices are similar to their rational counterparts in terms of risk-taking.

Our second prediction, labeled **"Competitiveness Reversals"**, states that the DC Model is often more likely to rank more competitive colleges at a lower position, at times generating dominated choices where the applicant ranks a lower-quality college higher on her list of choices.

While these two predictions seem to be in line with our previous observation from students' risk taking behavior in the administrative data, it is important to recognize that horizontal preference – i.e., preferences that do not align with competitiveness – may also contribute to the seemingly anomalous risk-taking behavior. To that end, the next two predictions play a key role in distinguishing our model from the alternative hypotheses.

Our third prediction, labeled **"Framing Effect"**, indicates that the DC Type takes more risks if the ROL problem is transformed to mathematically equivalent lottery formulation. We analyze the incentivized questions from the online survey to test this prediction. Estimates using our preferred specification suggest that 50.4% (SE=1.7%) of the students behave according to the predictions of the DC Type in our survey sample. Moreover, echoing our findings in the administrative data, a 1 SD increase in our socioeconomic status index is associated with a 5.3% (SE=1.8%) decrease in propensity to be the DC Type.

Our fourth prediction, labeled **"Upward Movement"**, implies that, if the priority score for a rational type was to increase, any listed colleges will move down along the list. For DC decision-makers, however, any listed college would first move up along the list, and then

risk-taking consideration. Artemov et al. (2017) posit that, in a strategy-proof environment, the mistakes on the lists are primarily inconsequential. Shorrer and Sóvágó (2018) find that, in Hungary, dominated choices in college applications are more likely to be made when expected cost is lower; they argue that multiple imperfections in decision-making may contribute to their findings. Hastings and Weinstein (2008) document substantial presence of information frictions in school choices, using randomized interventions. In a setting with strategic considerations, Rees-Jones et al. (2020) find that decision-makers neglect correlation in admission chances, even in settings where correlation is of first-order concern. Kapor et al. (2020) document mistaken beliefs using survey data in centralized system applications, using survey data. Dreyfuss et al. (2019) proposes that Koszegi-Rabin expectation-based reference dependence may explain the dominated choice in Li (2017)'s experimental data.

move down, exhibiting an inverse-U shape as a function of the priority score. Data analysis reveals substantial presence of the non-monotonic movements that are predicted by the DC Model.

To quantify the impact of the DC Model, we structurally estimate a mixture model of college choices, where both DC and Rational Type coexist, using simulated method of moments. We are able to jointly identify preferences and the DC Type by exploiting how risk-taking behaviors in different positions of the list jointly respond to variation in priority scores, which causes a differential rate of change in assignment probabilities for different colleges.

The mixture model fits the data better than the single-type model, even when extra flexibility is corrected by BIC analogues, and it yields substantially better out-of-sample predictions relative to the single-type rational model. A closer look at the fit of a Rational Type-only model suggests that the flexibility of college preference in our model generates less cautiousness and fewer competitiveness reversals, echoing our first two predictions.

The estimated share of the DC Type is substantial, and ranges from 45.1% (SE=0.54%) to 55.1% (SE=0.55%). The estimates are comparable to the share of the DC Type estimated from the survey experiment. Moreover, a 1 SD increase in the socioeconomic index is associated with a decrease that ranges from 3.68% (SE=0.56%) to 6.02% (SE=0.55%) in the share of the DC Type. In a counterfactual scenario where all students act optimally with respect to the mechanism, conditional on priority scores, the outcome gap between the most disadvantaged and advantaged quarter of the sample shrinks by 83.15%, suggesting that behavioral bias is the primary factor that explains the less desirable outcomes among high-achieving disadvantaged.

The DC decision rule also has adverse impact on overall efficiency. The de-biasing intervention is predicted to induce substantial welfare gain among behavioral applicants, which is on average larger than an increase of roughly 0.25 s.d. in the test scores under the old equilibrium. On the other hand, switching to either an unlimited list or a Boston mechanism without de-biasing, while intuitively making the bias less relevant, decreases welfare overall, echoing Chen and Kesten (2017)'s theoretical findings on the benefit of China's parallel mechanisms.

Our paper adds to the literature on behavioral mechanism design (Hassidim et al., 2016; Li, 2017; Rees-Jones and Skowronek, 2018; Dreyfuss et al., 2019). Our results suggest that decision-makers may fail to achieve optimality even if they recognize the gain of being strategic, an important difficulty discussed by Pathak and Sönmez (2008). We show that, in the presence of choice interdependence, a specific decision heuristic that neglects such a connection can better explain participants' strategies. Our analysis demonstrates the benefits of structural modeling in the analysis of behavioral agents (DellaVigna, 2018).

The paper also is closely related to the recent surge of studies on empirical student-school matching. Song et al. (2020), an important and closely related paper, shows that full rationality with no aggregate uncertainty is incompatible with admission outcome data in China. To tackle aggregate uncertainty, a key component of decision-making in centralized systems, as well as to provide evidence on the specific suboptimal strategy employed in our setting, our paper is similar to papers that employ both rank-order lists and survey data to test for optimal strategic play (De Haan et al., 2015; Kapor et al., 2020). Our paper further demonstrates that behavioral decision rules can be easily incorporated into the framework of revealed preference analysis laid out in Agarwal and Somaini (2018, 2019), and can help unmask the mechanisms behind the choice patterns of high-achieving disadvantaged students (Hoxby and Avery, 2012). Our findings suggest that certain cognitive limitations create gaps in admission outcomes among applicants of the same academic ability; thus, our work is related to the literature on the distributional consequences of behavioral biases (Campbell, 2016; Bhargava et al., 2017; Allcott et al., 2019; Rees-Jones and Taubinsky, 2020). While the underlying mechanism is different, this also echoes studies that cover the distributional impact of school choices in decentralized systems (Walters, 2018).

The paper proceeds as follows. Section 2 introduces the empirical setting and data sources. Section 3 lays out the problem mathematically and discusses both the Rational Rule and the DC Decision Rule. Section 4 presents the evidence concerning Cautiousness and Competitiveness Reversals. Section 5 tests Framing Effects using the survey experiment data. Section 6 tests Upward Movement using the administrative data. Section 7 presents results from the structural estimation. Section 8 concludes.

2 Empirical Setting

2.1 Summary of Timeline

Figure A1 presents the timeline of the admission procedure[6]. Student applicants are required to take the College Entrance Exam (CEE), a nationwide exam that takes place less than one month before the start of college admissions. As elaborated in Appendix E.2, the exam performance determines students' priority scores in the admission system and thus has a predominant impact on students' application strategies.

When students are notified of their test scores and corresponding provincial rankings, the

[6] The timeline in 2020 is different from the years before 2020 because of COVID-19. In 2020 the exam as well as all the related admissions activities were postponed by exactly one month.

online college application system opens. At that time, students know whether their score meets the minimum requirement to apply for schools in the 1st-tier college category, which is set by Ningxia Provincial Education Authorities. It has remained quite stable in terms of rankings over time[7].

The application process is time-constrained and cognitively demanding. Students need to select four colleges from 239 colleges, but have few opportunity to learn about this system by trial and error before submitting their final decisions, despite the novelty of this decision environment. Anecdotal evidence suggests that misunderstanding is not rare. According to several college application advisory platforms on the Chinese Internet, one of the most common mistakes is to treat the four spots on the ROL as separate and equal, effectively ignoring the order in which the ROL is processed[8].

2.2 Admission Rule

After the deadline for ROL submission, the centralized admission system assigns students to colleges using a deferred acceptance algorithm based on their priority score and the colleges' preannounced admission quotas. Since the priority score for each student is the same for all colleges, the mechanism is effectively a serial dictatorship mechanism, where colleges only need to specify a priority score cutoff to decide which applicants are admitted, regardless of a college's position on the student's submitted ROL. For a student applicant, she knows her priority score and ranking when she applies, and past cutoff scores are publicly available. The only uncertainty comes from the cutoffs of the current year.

Table B1 presents examples of how cutoffs determine admission outcomes. In Example 1, the student is admitted to college A because her score exceeds A's cutoff. The system ignores all her lower-ranked choices. In Example 2, the student is admitted to college B because her score does not meet A's cutoff but exceeds B's cutoff. As a result, the system assigns her to B, ignoring C and D. In Example 3, the student is unassigned because she does not meet the cutoff of any college she listed. In Example 4, the student is assigned to college D because she does not meet the cutoffs of A,B, and C but meets the cutoff of D.

After assignment of first-tier colleges has been completed, students are notified of the admission decision within a month. Students who are not admitted to any first-tier colleges will be passed on to the next stage of admission, where the centralized system will assign them to lower-tier colleges using the same priority score and similar algorithms [9].

[7] See Appendix E.1 for additional details on college category.

[8] See here for an example of comments about mistakes in college applications (in Chinese).

[9] Students can rank four second-tier colleges and four third-tier colleges

2.3 Data

The first dataset is the administrative data generated by the centralized admission system that records the application behavior of students from 2014 to 2018. This dataset is maintained by the Ningxia Provincial Education Authorities. The second dataset is an online survey experiment that we set up in 2020. It also targets CEE takers in Ningxia applying to first-tier colleges, the same group of students we analyze in the administrative dataset.

(I) Administrative Data We obtained access to administrative data from 2014 to 2018, covering around 9,000 first-tier eligible science track students in each admission cycle. The number is considerably lower for humanities track students, amounting to roughly 2,000. The data contains students' CEE scores, ROLs, admission outcomes, and some demographic information, including the county, city and street of their residence address (available only in 2015, 2017, 2018).

(II) Online Survey In August 2020, we carried out an online survey that targeted high school students who had applied for first-tier colleges in 2020. Four local high schools actively encouraged students to take our survey. As a result, while any first-tier eligible applicants in Ningxia could respond to our online survey, our sample mainly consists of students from these four high schools. We were able to collect 1,412 complete and effective responses, roughly 15% of the total number of first-tier college applicants in 2020. As shown in Figure A1, the survey was conducted right after students submitted their ROL for first-tier colleges, but before they were notified of the admission outcomes[10]. The survey consisted of three parts. The first part elicited basic information, such as their final ROL, high school, gender, age, parents' education and occupation, CEE score, source of application advice, and preferences over college characteristics. The second part elicited their beliefs about the unconditional admission probability[11] of the colleges on their ROL ($0\% \sim 100\%$) and how satisfied they would feel (0-100) if they were admitted to a particular college. The third part consisted of several incentivized risk-taking questions that were presented in the form of a ROL and lottery, which are discussed in detail in Section 5.2.

[10]We choose this particular timing for three reasons. First, in order to best approximate students' information set, the survey had to take place after students had been notified of their score and had spent time researching colleges. Second, high school officials believed that the survey might distract some students from the high-stakes and time-sensitive application process, so we postponed the survey until after the college application deadline.

[11]The question asked students to guess the probability of meeting the admission cutoff of the college in question. Based on feedback from teachers and students in a pilot, admission cutoff is a very basic concept. The most natural way to elicit beliefs about admission probability was to ask students about their belief that their scores would meet the admission cutoffs.

3 Decision Problem

3.1 Setup and Mathematical Notations

To mathematically describe the decision problem in our setting, consider a student, Mei, who needs to list four colleges from a set of n colleges on her ROL. After she submits her ROL, along with other students, the centralized admission system will process their ROLs using the Constrained Deferred Acceptance Algorithm (DAA). Then, Mei either will be assigned to one of the four colleges that she listed on her ROL, or will be rejected by all four colleges and end up with her outside option. We assume that the number of students m is much larger than the number of colleges, n.

Mei is playing an incomplete information game[12], where she does not know the ROLs submitted by other students and has to form beliefs about what the other lists could be. As discussed in Section 2.1, because students have been notified of their scores and corresponding provincial rankings when they apply, the admission outcomes solely depend on the cutoffs of the colleges that they apply for, unknown at the time of list submission. Hence, instead of thinking about others' lists, Mei only needs to form her beliefs about the distribution of cutoffs.

Based on beliefs about the distribution of cutoffs, Mei will assign probabilities of meeting the cutoffs of the n colleges that she is contemplating. Denote the probability of vacancy availability (i.e.,unconditional assignment probabilities or probability of meeting the cutoff) of the n colleges by p_1,p_2,...,p_n respectively. For the purpose of presentation and without loss of generality, assume that $p_1 < p_2 < ... < p_n$ (that is, colleges are ranked from the most competitive ones to the least). Denote the utility of admission to colleges by u_1, u_2, ..., u_n respectively. The utility of Mei's outside option is $\underline{u}$. For any single college j, the only two characteristics that Mei needs to care about are its admission utility u_j and unconditional admission probability p_j.

3.2 Estimate Probability p_j from Data

As discussed in the previous subsection, one of the two components of this decision problem is the unconditional probability p_j, for which we need to construct measures to approximate what students think. To that end, we proxy students' beliefs using admission cutoffs in the past, which are publicly available shortly after the end of each previous admission cycle[13].

[12]This treatment is conventional in this literature. Examples include Agarwal and Somaini (2018); Kapor et al. (2020); Calsamiglia et al. (2020).

[13]See here for a well-known website that documents past admission cutoffs.

The cutoffs in past years can reliably predict the current cutoffs. In Figure 1, we plot the cutoff in its converted form in a specific year (e.g., 2018) against the cutoff the previous year (e.g., 2017) for all the colleges that admitted Ningxia students during this time period. We find that the correlation between a cutoff and its past year counterpart is around 0.95; it would be even higher, except that a few outliers significantly drag the correlation down. The median of the distance between realized cutoffs and the college-level average during 2014-2018 is 0.097 of a standard deviation of priority scores among science-track applicants, and 0.146 of a standard deviation of the distribution among humanity-track applicants. Importantly, the uncertainty is larger among less competitive colleges, as the scatter at the bottom left of each graph is more likely to be away from the 45-degree line.

To calculate probabilities, we assume that for college j, in year t, the cutoff c_{jt} is normally distributed:

$$c_{jt} \sim N(\mu_j, \sigma(\mu_j))$$

where the value of μ_j is the average of admission cutoffs for college j during 2014-2018, which reflects the overall competitiveness of a college across years. The assumptions about the value of μ_j are motivated by the informativeness of past cutoffs. We compute the distribution of $c_{jt} - \mu_j$ in Figure A2a, and find that the distribution function is a bell-shaped function that is centered around zero, with reasonably thin tails, suggesting that it is possible to approximate the true distribution with a hybrid of normal distributions.

Based on the observation from Section 1 that the predictability is heterogeneous across colleges of different competitiveness, we assume that the mean of $ln(\sigma_j)$ is a fourth-order polynomial of μ_j:

$$E[ln(\sigma_j)|\mu_j] = \beta_0 + \sum_{k=1}^{4} \beta_k \mu_j^k$$

We estimate the model using maximum likelihood, for the science and humanity tracks, respectively. We then use the estimated $\hat{\beta}$ to predict σ_j:

$$\hat{\sigma_j} \equiv exp(\hat{\beta}_0 + \sum_{k=1}^{4} \hat{\beta}_k \mu_j^k)$$

With the estimation, the probability of meeting the cutoff of college j is:

$$\hat{p}_{ij} \equiv \Phi(\frac{s_i - \mu_j}{\hat{\sigma_j}})$$

where $\Phi(.)$ is the CDF of standard Gaussian.

We follow Kapor et al. (2020) to validate the estimates of admission probabilities. Specifically, we analyze individual level data on admission outcomes by running the following regression:

$$1(\text{Admitted to First Choices})_i = \alpha_1 + \beta_1 \hat{p}_{ij}$$

where subscript j represents students' first choices. The null hypothesis that the estimated admission probability is accurate implies that $\alpha_1 = 0$ and $\beta_1 = 1$.

The results suggest that our estimates provide a reasonable approximate to actual probability. As shown in Columns (1) and (2) of Table B2, $\hat{\alpha_1} = 0.0056$ (SE=0.0024) and 0.0019 (SE=0.0041) for the science and humanity tracks, respectively, and $\hat{\beta_1} = 0.9997$ (SE=0.0043) and 0.9954 (SE=0.0084) in the science and humanity tracks, respectively. While the null hypothesis is statistically rejected for the case of science track, the deviation from null hypothesis is quantitatively small. In Figure A2b, we divide colleges into four groups of equal size according to their competitiveness and plot the kernel density estimation of the distribution of $c_{jt} - \mu_j$ for each group respectively. The figure shows that our model can well approximate such empirical patterns.

3.3 The Optimal Rank-Order List

Given the beliefs about the unconditional admission probability of colleges, as well as the utility of admission for each college, playing Bayesian Nash Equilibrium in this context reduces to finding out the optimal portfolio for Mei. Specifically, suppose that Mei's ROL is (j_1, j_2, j_3, j_4), and the utilities and probabilities are (u_{j_1}, p_{j_1}), (u_{j_2}, p_{j_2}), (u_{j_3}, p_{j_3}), (u_{j_4}, p_{j_4}), respectively. Given her list, she will be admitted to college j_1 with probability p_{j_1}. Under constrained DAA, she will be considered by college j_2 only when college j_1 has rejected her; thus, the probability of being admitted to college j_2 is $(1 - p_{j_1})p_{j_2}$[14]. Similarly, the probabilities of being admitted to colleges j_3 and j_4 are $(1-p_{j_1})(1-p_{j_2})p_{j_3}$ and $(1-p_{j_1})(1-p_{j_2})(1-p_{j_3})p_{j_4}$, respectively. Her expected utility from the portfolio $\{j_1, j_2, j_3, j_4\}$ is:

$$\begin{aligned} EU([j_1, j_2, j_3, j_4]) \equiv p_{j_1}u_{j_1} + (1-p_{j_1})p_{j_2}u_{j_2} + (1-p_{j_1})(1-p_{j_2})p_{j_3}u_{j_3} + (1-p_{j_1}) \\ (1-p_{j_2})(1-p_{j_3})p_{j_4}u_{j_4} + (1-p_{j_1})(1-p_{j_2})(1-p_{j_3})(1-p_{j_4})\underline{u} \end{aligned} \tag{1}$$

Considering joint assignment probabilities for a group of colleges at the same time substantially complicates the decision problem because the chance of admission at one college

[14] Here we are assuming that admission probability is independent because we believe that this is a reasonable approximation in our empirical setting. See Section E.3 for a detailed discussion of why this assumption is justified.

depends on the chance of admission at the colleges that the student has ranked above it. This interdependence implies that decisions should not be made by considering each program sequentially, viewed in isolation. Instead, Mei should consider admissions probabilities arising from a complete ROL, and thus optimal decision-making requires picking an optimal portfolio out of a large number[15].

To understand what an optimal portfolio should look like, suppose Mei's best list is $[a^*, b^*, c^*, d^*]$. The risk taking behavior depends on Mei's preference profile

Vertical Preferences In case of vertical preferences (i.e. higher risk is associated with higher desirability), we know that $p_{a^*} < p_{b^*} < p_{c^*} < p_{d^*}$, a qualitative prediction that we can directly test using the administrative data alone. The optimal amount of risk to take is different across positions. For example, p_{d^*} needs to maximize $p_d u_d + (1 - p_d)\underline{u}$, whereas p_{a^*} needs to maximize $p_a u_a + (1 - p_a)EU([b, c, d])$. The fact that $EU([b, c, d]) > EU(\emptyset) = \underline{u}$ implies that Mei needs to worry less about the downside of missing the risky college she pursues (i.e., the utility that follows $(1 - p)$ in each expression). Consequently, it is the colleges that the student ranks below the current choice, not the colleges ranked above it, that matter most for the optimal choices. Hence, backward induction, a decision rule unnatural to human cognition, becomes useful in this process:

- (blank) $\rightarrow$ (blank) $\rightarrow$ (blank) $\rightarrow$ d $\rightarrow$ (outside option)
- (blank) $\rightarrow$ (blank) $\rightarrow$ c $\rightarrow$ d $\rightarrow$ (outside option)
- (blank) $\rightarrow$ b $\rightarrow$ c $\rightarrow$ d $\rightarrow$ (outside option)
- a $\rightarrow$ b $\rightarrow$ c $\rightarrow$ d $\rightarrow$ (outside option)

Horizontal Preferences In this case, we can no longer deduce $p_{a^*} < p_{b^*} < p_{c^*} < p_{d^*}$ from $u_{a^*} > u_{b^*} > u_{c^*} > u_{d^*}$, because, if any pair of colleges j_1 and j_2 that reflect Mei's horizontal preference are both present on the list, the more competitive one, which is less desirable in terms of Mei's preference, would be ranked lower.

Optimal Decision Rule Regardless of Preferences Chade and Smith (2006) find that a decision rule, Marginal Improvement Algorithm, can achieve the global optimum by selecting one college at a time. In each step, the optimum depends on the colleges that have already been included in the portfolio in previous steps. The procedure coincides with backward induction in the case of strong vertical preferences, while the mapping between

[15] To be precise, the number is $\binom{n}{4}$, which amounts to 4 billion in our context.

step number and list position becomes more complicated for other preference profiles. The commonality, however, is that the decision needs to be converted into a dynamic problem where the current choice is interrelated with the choices in the past steps.

3.4 Formulation of the Directed Cognition Model

The rational benchmark in Section 3.3 proposes that the optimal portfolio can be reached by decomposing the problem into four different discrete choice problems. The correct decomposition of this problem requires student applicants to appreciate the interdependence between choices, because it is the colleges that they list below a given rank, not those above that rank, that affect the optimal choice for the given rank. Literature in experimental economics, however, has established that, even in simplified settings, subjects have trouble grasping the concept of backward induction (Camerer et al., 1993; Johnson et al., 2002). Moreover, laboratory evidence suggests that decision-makers lack the ability to cope with uncertainty in simple decisions (Martínez-Marquina et al., 2019), a skill that is necessary to assess the distribution of utility for the lower-ranked choices.

In this subsection, we continue to use the setting in Section 3, and introduce an alternative boundedly rational decision rule that is inspired by the Model of Directed Cognition in Gabaix et al. (2006) (the DC Model). We believe that this decision rule explains students' suboptimal strategies when they cannot apply the optimal strategy as prescribed in Chade and Smith (2006). The rule prescribes that, instead of tracking all the information and acting optimally upon it, another student applicant, Hua, due to cognitive limitations, myopically focuses on the spot where he is actively contemplating which college to fill in, and neglects the impact of that choice on the rest of the list. He fills out his ROL in a natural order, from the first choice to the fourth choice. Mathematically, in step i, Hua maximizes

$$p_i u_i + (1 - p_i)\underline{u} \tag{2}$$

As a result, in each step Hua is making choices for essentially the *same* decision problem. That is, he maximizes the expected utility of a portfolio that consists of his current choice and the perceived outside option, as described graphically below:

- **Step 1**: $j_1 \rightarrow$ (blank) $\rightarrow$ (blank) $\rightarrow$ (blank) $\rightarrow$ (Outside Option)
- **Step 2**: $j_1 \rightarrow j_2 \rightarrow$ (blank) $\rightarrow$ (blank) $\rightarrow$ (Outside Option)
- **Step 3**: $j_1 \rightarrow j_2 \rightarrow j_3 \rightarrow$ (blank) $\rightarrow$ (Outside Option)
- **Step 4**: $j_1 \rightarrow j_2 \rightarrow j_3 \rightarrow j_4 \rightarrow$ (Outside Option)

This decision rule requires less cognitive capacity for two reasons. First, Hua is proceeding in a natural order by considering the first choices before the rest of the ROL. Second, because Hua is making choices for each spot in isolation, the source of uncertainty is reduced and he only needs to consider at most two states: admission to a first-tier school, or rejection by all four of his choices and getting the utility of the outside option.

4 Summary Statistics on Risk-Taking Behavior

Section 3.3 and 3.4 have introduced both the Rational Rule and the DC Rule. They yield different predictions regarding basic risk taking behavior on the list, which are discussed in Section 4.1. We present data analysis that supports the presence of the DC Rule in Section 4.2 and Section 4.3.

An important feature of our setting is that some students who barely meet the minimum requirement of first-tier colleges have limited options because of their low priority score. Therefore, mechanically they are much more risk-taking than those whose priority score is above the minimum by a comfortable margin. We therefore focus on the top 60% in this and subsequent sections[16].

4.1 Predictions: Cautiousness and Competitiveness Reversal

Compared to the rational decision rule, the DC decision rule yields substantially different predictions about the patterns of risk taking. To mathematically describe the differences between the rational benchmark and the DC Rule, consider Hua, who is choosing between two colleges, a or b, to list as his choice in the qth spot. College a is more desirable and riskier than b, thus $p_a < p_b$. Hua needs to compare $U_a \equiv p_a u_a + (1 - p_a)PF_q$, the expected utility of choosing a, to $U_b \equiv p_b u_b + (1 - p_b)PF_q$, where PF_q is the perceived expected utility of a portfolio that consists of all the choices below the qth choice, including the outside option. Define the propensity to take risk as a function of spot position (i.e. the qth choice) and the decision rule (Optimal or DC)

$$f(q, \text{decision rule}) \equiv U_a - U_b = p_a u_a - p_b u_b + (p_b - p_a)PF_q$$

Here, the greater $U_a - U_b$ is, the more appealing it is to take risks and choose a.

[16] Figure A3a presents the bin-scatter plot of the mean probability for the four choices conditional on the quantile of priority score. We can see from the figure that, for the bottom 5% in terms of priority score, even the mean probability of the fourth choice is less than 20%, as these students really don't have any safe choices. The mean probability for all the four choices rises simultaneously, with this trend stopping when the priority score quantile is around 40%.

Prediction 1 (Top-Choice Cautiousness) *For any choice $q < 4$, the Rational Rule takes more risks in listing their first choice than the DC Rule. Moreover, the gap in risk-taking between the Rational and the DC Type is decreasing in q.*

.

This prediction holds because Mei can correctly calculate the expected value as $PF_1 > PF_2 > PF_3 > PF_4 = \underline{u}$, whereas Hua ignores the rest of the portfolio and makes decisions as if $PF_1 = PF_2 = PF_3 = PF_4 = \underline{u}$. Mei's cautiousness is as great as Hua's in the fourth spot. As $U_a - U_b$ is increasing in the expected utility of the backup list, Mei is more inclined than Hua to make a risky move for higher-ranked spots. The risk-taking gap between the DC Rule and the Rational Rule will be maximal for the first spot.

Under the assumption of vertical preferences, the DC decision rule also has implications for the order of admission probability for the listed colleges:

Prediction 2 (Competitiveness Reversals) *Under vertical preferences, the ROL of the Rational Type always features decreasing utility and increasing admission probability (that is, $u_a > u_b > u_c > u_d$, $p_a < p_b < p_c < p_d$). A DC Type, in contrast, may exhibit "risk-taking reversal" by putting a riskier college in a lower-ranked position, leading to dominated choices.*

This prediction holds because, for Mei, riskier colleges should also be put in higher-ranked positions. For Hua, however, $f(i, \text{Rational}) = f(j, \text{Rational})$ because only the outside option is regarded as his backup list. For example, Hua may list c before d, not because c is more desirable, but because its probability is higher: $p_c u_c + (1 - p_c)\underline{u} > p_d u_d + (1 - p_d)\underline{u}$.

4.2 Summary Statistics on Admission Probability

Distribution of Admission Probability for the Four Choices Table 1, Panel A presents the summary statistics of unconditional admission probability that we construct as described in Section 3.2, for each choice on the lists. The mean probability for the first and fourth choices is 45.96% and 90.90% respectively, consistent with the prediction from the rational benchmark that students should be pursuing more risks for top choices.

However, substantial share of students are not taking risks in their first choices, as the 75th percentile of probability is 84.30%. On the other hand, the heterogeneity of probability is minimal for the fourth choices, where the 25th percentile is 95.52%, suggesting that the vast majority of students are taking little risk for their bottom choices, which makes sense in a high-stakes environment.

Share of "Competitiveness Reversal" The rational decision rule and vertical preferences jointly predict that the probability should be lower for the higher-ranked choices. To quantify students' strategy in this dimension, we construct risk-taking reversal, namely, a "flip" of the probability of colleges, to quantify the violation of benchmark prediction. As our goal is to capture risk-taking reversal anywhere on the ROL, we consider the following statistics:

$$R \equiv max_{j>i}\{p_i - p_j\}$$

In the expression of R, we take the maximum for the probability gap between any pair of choices to capture the most serious competitiveness reversals on the ROLs. We report the results in Table 2, Panel A, and find that 61.51% of the ROLs exhibit competitiveness reversals ($R > 0\%$). Further limiting our scope to the case of "serious" reversals, where an ROL is counted only when R exceeds a certain positive threshold ($R\% > 25\%$,$R\% > 50\%$,$R\% > 75\%$), the share mechanically decreases but remains non-negligible. For example, the share is 23.74% when the restriction is $R\% > 25\%$.

In summary, the data suggests that a substantial proportion of students are quite cautious even for their first choices, and many of them exhibit "competitiveness reversals" on their lists. This clearly rejects the joint hypothesis that students have perfect vertical preferences and are following the rational benchmark.

4.3 Socioeconomically Disadvantaged Exhibit More Top-Choice Cautiousness and Competitiveness Reversals

A large literature documents that socioeconomically disadvantaged students are worse at strategizing in centralized systems (Lucas and Mbiti, 2012; Ajayi, 2013; De Haan et al., 2015; Shorrer and Sóvágó, 2018; Kapor et al., 2020). We choose average educational attainment at township level to approximate socioeconomic status[17]. We match the township level educational attainment data to individual students in the administrative dataset, and plot the distribution of this measure in Figure A4. We split students into four groups according to their SES, and focus on the most advantaged quartile and the most disadvantaged quartile. Because Ningxia accounts for only about 0.7% of China's area, and all but two first-tier colleges are located far outside the province, the difference in township should not significantly alter geographic proximity.

[17] Roughly speaking, township is equivalent to zip code in the US. We obtain statistics on average years of education among adults between 40-65 at township level from the China Census in 2010, as well as access to students' home addresses in 2015, 2017, and 2018.

In Figure 2a, we compute the statistics in Section 4.2 for the most advantaged and the most disadvantaged quartile, respectively. The mean probability of the first choices among the socioeconomically disadvantaged students (54.6%) is less than their advantaged counterparts (44.7%). However, for their fourth choices, the probability among the disadvantaged (92.1%) is slightly less than their advantaged counterparts (92.7%) [18].

We run the following regression to quantify the difference statistically:

$$\text{Outcome} = \beta\text{Disadv} + f(\text{Priority Score}) + \text{Disadv} * g(\text{Priority Score}) + \text{controls} \tag{3}$$

where Disadv indicates whether students are from a lower SES group, and f(Priority Score) and g(Priority Score) represent a fourth-order polynomial of priority score[19]. The main effect of Disadv, β, is the overall outcome gap between students of different SES groups after priority score has been fully controlled, as well as the heterogeneity in whether the outcome gap changes with the priority score.

As shown in Table 1, Panel B, the results confirm our visual perception regarding the first and fourth choices. After a full set of controls is introduced, the gap between the advantaged and the disadvantaged with regard to fourth-first choice probability differences amounts to 9.13% (SE 0.75%). Panel C demonstrates that the gap is robust to priority score.

Figure 2b plots the share of reversals for the most advantaged and disadvantaged quartiles, respectively. The gap in the share of reversals between disadvantaged and advantaged remains about the same, and is robust to the threshold. When the threshold $X\%$ is 25%, for example, the share of reversals among the advantaged is 19.1%, and the weighted share of reversals among the disadvantaged is 22.9%, roughly 20% higher than the advantaged.

In Table 2 we plug in "share of reversals" as the outcome variable in Equation 3. In each column, we vary the threshold X so that it equals 0, 25, 50, or 75% in Columns 1, 2, 3, and 4, respectively. As reported in Panel B, the results are consistent with the graphical observation, with the gap in the share of reversal remaining at about 5%; as Panel C shows, the results are robust to the level of priority score.

To examine whether the admission outcomes are worse among the disadvantaged, we run the following regressions:

[18] All the statistics in Figure 2 have been reweighted to take into account any differences in priority score. Please refer to Figure A3b for a complete breakdown of admission probability by priority score, across students in the most advantaged and most disadvantaged quartiles.

[19] Each of the terms in the polynomial has been demeaned so that the main effect β is the predicted Adv-Disadv Gap at average level of priority score.

$$\text{Selectivity of Admitting College} = 1(\text{SES Quartile}) + f(\text{Priority Score}) + \text{Controls}$$

where we measure the selectivity of the admitting college by calculating the average admission cutoffs for the colleges during 2014-2018. We report the regression results in Table B3, Panel A. The results in Column 1, for example, suggest that the most disadvantaged quartile (1st Quartile) on average end up in colleges whose selectivity is 0.1288 (SE=0.0082) of a standard deviation worse compared to the most advantaged quartile (4th Quartile).

5 Survey Experiment: Testing Framing Effect

The DC Model generates more first-choice cautiousness and competitiveness reversals. Evidence in Section 4 seems to indicate that the risk-taking behavior of many applicants is in line with what is predicted by the DC Model, and that the DC Type may be more prevalent among the disadvantaged. However, risk-taking behavior can also be affected by horizontal preferences, information frictions, or subjective beliefs.

To tackle these issues, we design a survey experiment in which students make college and lottery choices. The monetary incentive and risk of these hypothetical colleges are designed to test the predictions of the DC Rule that are not susceptible to college preferences, beliefs about assignment probability, or information frictions in real college choices.

5.1 Prediction: Framing Effect under Arbitrary Preferences

Consider what leads to a DC Type's suboptimal strategy. The correct utility of choosing college a for the rth choice is

$$U_a \equiv p_a u_a + (1 - p_a) U_r$$

where U_r is the expected utility of the portfolio that consists of everything below the rth choice on the list. A DC Type's trouble is that, when the question is presented in a ROL, they fail to calculate U_r and instead treat it as u_0. When this is not presented in the form of a ROL question, but in the form of the mathematically equivalent lottery choice $(p_a, u_a; (1 - p_a), U_r)$, the payoff in the event of rejection has been calculated and presented clearly so that the DC Type cannot distort it. Effectively, choices presented in the form of a lottery can "de-biased" by bringing the utility of backup choices to the decision-makers' attention so that their cognition is no longer directed to a single spot. Let U_r' denote the perceived expected utility of the portfolio that consists of everything below the rth choice. Mathematically, this prediction holds because, for the Rational Type, $U'_r = U_r$, regardless of whether the problem is presented in lottery representation or ROL representation. For the DC Type, $U'_r = U_r$ if it is presented in lottery representation, but $U'_r = u_0 < U_r$ if it is presented in the ROL representation. Hence, we have the following prediction:

Prediction 3 (Framing Effect) *Suppose all the possible portfolios that are framed as ROL have been correctly transformed into their lottery representation. A Rational Type will behave consistently across ROL and lottery questions. By contrast, the DC Type will be more risk-taking in the lottery questions.*

5.2 Design of the Survey Experiment

The core of the survey experiment consists of three groups of incentivized questions. The first and third group of questions asked students to choose the amount of risks they prefer in each hypothetical situation. They need to choose between College X and College Y, whose unconditional admission probability and payoffs in the event of an "admission" in the game have been specified in Panels A2 and C2 of Table B4, respectively, and fill in the first spot of the ROL. For each multiple price list, there are seven questions in total, as presented in the table, where the payoff of X is held constant (admission probability is 50%, get 25 CNY if "admitted" in this scenario), and the payoff of Y is in increasing order (admission probability is 25%, get 30, 35, 40, 45, 50, 55, 60 CNY if "admitted" in this scenario). The second, third, and fourth spots of the ROL have been pinned down, as shown in Panel A1 and C1 of Table B4, where one of them will definitely "admit" the student applicant if she is not "admitted" to the first spot. The rules of admission for both groups of questions are exactly the same as the real admission procedures, with the only difference being that the payoff of being "admitted" to lower ranked colleges in Question Group 1 is 20 Chinese Yuan (CNY), whereas the amount in Question Group 3 is merely 5 CNY. These binary choice problems feature the core tradeoff in our setting: if students wish to take more risks and choose a more desirable college for their first choices, they must face a greater risk of being admitted to backup choices, whose payoffs are considerably lower.

The second group of questions is mathematically equivalent to the first one, but is asked in the form of its lottery representation. This group has seven questions as well. Lottery X, whose payoff structure is (25 CNY, 50%; 20 CNY, 50%) delivers the same distribution of payoffs as College X in Question Group 1, and is held across questions. The payoff structure of Lottery Y is (30 CNY, 25%; 20 CNY, 75%), (35 CNY, 25%; 20 CNY, 75%), ... (60 CNY, 25%; 20 CNY, 75%), respectively, which is mathematically equivalent to the payoff of College Y in Question Group 1. In terms of framing, however, Question Group 2 differs from Question Group 1 in that the probability and payoff of rejection from the first choice are included in the choices, as shown in Panel B of Table B4. Because the DC Type in our setting choose their first college in isolation, they ignore the payoff of lower-ranked colleges, and thus fail to translate the ROL problem to its correct lottery representation. The inclusion of downside payment in the lottery precisely mutes the mistake from the DC decision rule.

Students were directed to carefully read through our explanations about the questions and complete comprehension checks before answering these questions. Since the payoff of College/Choice X is held constant, whereas that of College Y is increasing, a coherent response could switch from X to Y at most once. This point is clearly communicated in the instructions and students are allowed to switch from X to Y at most once in their responses.

After the student applicants have submitted their ROLs during the experiment, we asked them more application-related questions. The key questions which we intend to discuss are listed below:

1. The ROL that they submit.
2. For each choice, what do they think is the chance of meeting its cutoff?
3. If only two colleges were allowed to be included in a list, which two would they choose?
4. If only one college was allowed to be included in a list, which college would they choose?

5.3 Analysis of Survey Data

Prediction 3 states that DC Type students appear to take less risk in ROL questions compared to their (mathematically equivalent) lottery representations. We start our analysis by tabulating the joint distribution of students' responses to Question Groups 1 and 2 in Figure 3. About 65.5% of the observations are located in the blue blocks, indicating that students are very cautious[20] in both rank-order list and its lottery equivalent questions, or not very cautious in both questions. Such behavior is consistent with, or does not substantially deviate from the Rational Decision Rule. Meanwhile, 30.8% of the students are very cautious in the college choice problem, but not in the lottery equivalent questions. Such behavior is indicative of the presence of the DC Type.

[20] As described in graph, being very cautious means that in terms of risk attitude, the students prefer (50,25%;20,75%) to (25,50%;20,50%). The implied CRRA coeffiient for such risk attitudes is larger than 20. Loss-averse with the fixed choice as reference point under small stakes as in Sprenger (2015) implies that the decision maker's loss aversion is larger than 6.35.

Table 3, Panel A reports whether students with disadvantaged SES backgrounds, as measured by parents' average years of education, is associated with the aforementioned behavior. Linear probability models with various sets of controls demonstrate that one standard deviation of increase in the normalized SES index is associated with 4.1% to 4.7% of increase in the probability of belonging to the red block (i.e. exhibiting substantial framing effect predicted by the DC Decision Rule). This also relates to previous findings from the administrative data in Section 4.3, where socioeconomically disadvantaged students are more cautious only in the top spots of their lists and commit more competitiveness reversals.

To estimate the share of the DC Type in the survey sample, we model survey takers' risk-taking behavior by assuming that students have power utility functions over money:

$$u = (c + B)^{\rho}$$

where B is background consumption, which we set to be 10 CNY[21]. The power utility curvature ρ are assumed to satisfy $0.05 \leq \rho \leq 1$, and can vary on Edu, parents' average years of education, and CEE, the quantile of Priority Score:

$$\rho = \min\{\max\{0.05, \alpha_0 + \alpha_1 \text{SES} + \alpha_2 \text{Score} + \epsilon_\rho\}, 1\}$$

where $\epsilon_\rho \sim N(0, \sigma_\rho^2)$.

The decision noise is added to the model by assuming that decision makers perceive choice Y noisily. The lottery of Choice X and Y in Question Group 2 is denoted by $\tilde{X}(20) \equiv (25, 50\%; 20, 50\%)$ and $\tilde{Y}(m, 20) \equiv (m, 25\%; 20, 75\%)$. For the Rational Type, the riskier choice $Y(m, b)$ and $\tilde{Y}(m, 20)$ is perceived as $Y(m+\epsilon, b)$ and $\tilde{Y}(m+\epsilon, 20)$ respectively, where $N(0, \sigma_\epsilon^2)$ is independent and identically distributed across individuals. For question 1 and 3, denote the lottery presentation of College X and Y by $X(b) \equiv (25, 50\%; b, 50\%)$ and $Y(m, b) \equiv (m, 25\%; b, 75\%)$, respectively, where m is the payoff of first choices and b is the payoff of backup colleges. For the Rational Type, they process the question correctly and recognize its lottery representation. The decision noise is added in the same way as Question Group 2. For the DC Type, the choices in Question Group 1 and 3 are perceived as $X(0)$ and $(Y(m, 0)$ respectively, resulting in more cautiousness. The decision noise is added to m in the same way. We additionally consider a third type that is established in the literature for some of our specifications: the "sincere type" (Pathak and Sönmez, 2008; Calsamiglia et al., 2020). The sincere type predicts that, in the ROL presentation, students will always prefer colleges with the highest payoffs, ignoring the probability of admission. The decision noise for this type is added to m, which is also the higher payoffs among choices. The variance

[21] Roughly the value of one meal in Ningxia.

of decision noise σ_ϵ^2 is allowed to be different across question groups, but assumed to be the same across different behavioral types.

We further assume in this mixture model that the share of the DC Type varies with socioeconomic status:

$$Prob(\text{DC Type}|\text{Edu}, \text{Score}) = \frac{exp(\beta_0 + \beta_1\text{SES} + \beta_2\text{Score})}{exp(\beta_0 + \beta_1\text{SES} + \beta_2\text{Score}) + 1}$$

We estimate this mixture model and present the main results in Table 3, Panel B. Including DC Type in the estimation (Column 2) substantially improves the fit (Log Likelihood = -8781.778, 9 parameters) compared to the model in Column 1 that only allows for the Rational Type (Log Likelihood = -9100.574, 6 parameters). The improvement is substantial, such that the Bayesian Information Criterion also favors the mixture model (BIC metrics = 17628.83) over the single-type rational model (BIC metrics = 18244.66). The impact of including the sincere type (Column 3), while it also improves the fit, is limited compared to the DC Type (Log Likelihood = -8780.909, 10 parameters). In line with this observation, the estimated share of the DC Type is 50.4% in our preferred specification. The marginal effect of socioeconomic status is also statistically significant, where a 1 SD increase in the SES Index is associated with a 5.5% (SE=1.8%) decrease in the share of the DC Type.

5.4 Framing Effect Predicts Risk-Taking Behavior in College Choices

If the DC Type indeed exists among the participants of the survey experiment, we would expect their real college choice patterns to exhibit what is described by Prediction 1 and 2 as well. Moreover, the DC Decision Rule is differentiated from the Rational Decision Rule by prescribing that decision-makers make choices in a forward way rather than doing backward induction when competitive colleges are mostly of higher desirability[22]. As a result, we would expect the DC Type to pick the top colleges, rather than bottom colleges as prescribed by backward induction, had they been allowed to include at most two colleges on their list.

Table 3, Panel C presents the mean statistics of students' college choices by whether they exhibit substantial framing effect (i.e. belong to the red block in Figure 3). It appears that applicants who are very cautious in the college choice problem but not in its lottery equivalents are substantially more likely to state that they would have picked their top choices in the original problem if the list is shortened such that they can only list up to one or two colleges. Moreover, these students are significantly more likely to believe that they have picked safer colleges for the top spot (i.e., top-choice cautiousness) but not for the

[22] As discussed in Section 3.3, in the presence of substantial horizontal preferences, there are exceptions when the Rational Rule does not imply backward induction

bottom spot, and that they have committed competitiveness reversals.

6 Testing Upward Movement

With administrative data alone, we show in this section that a particular variation in priority score will help differentiate the DC Model from various forms of horizontal preferences and other alternative hypothesis.

6.1 Prediction: Position Movement in ROL

This subsection presents another prediction that distinguishes the two decision rules with minimal parametric assumptions on college preferences. We characterize the choice pattern of any single college, A, as priority score (consequently, the assignment probability of A[23]) changes. For an arbitrary preference profile u (a utility vector that represents preferences over *all* colleges), if A appears on the list given a specific priority score s, where would A be if s were higher?

To understand the result intuitively, consider that, under the rational decision rule and preference u, A is a particularly attractive college and will appear on the list for some s. If s is too low, such that being admitted to A is impossible, A will be omitted because listing it wastes a spot. However, as s becomes higher, A appears on the list as soon as the admission probability is high enough. As s continues to move higher, more colleges become possible options for u. Consequently, A will remain in the same place if none of the newly possible options are better than A, and will move down the list if any newly possible option is better than A and has a favorable chance. Figure 4a presents an example in which the position of a college evolves as priority score changes. Note that, on the horizontal axis, priority scores have been converted to admission probability of A to make the graph comparable.

To mathematically describe the result, define function $\mathcal{R}$ that maps preference profile u, priority score s, college A to its position κ on the list under the rational decision rule:

$$\mathcal{R} : (u, A, s) \mapsto \kappa$$

where κ is 0 if A is omitted from the list. κ **takes the value of 4, 3, 2, 1 if** A **is the first, second, third, and fourth choice, respectively.** The following theorem characterizes $\mathcal{R}$:

[23]Probability of meeting the cutoff of A.

Theorem 1 *Under Assumption 1, 2, 3, for any preferences u, college A, and s_0 such that $\mathcal{R}(u, A, s_0) \geq 1$, if $s > s_0$, then $\mathcal{R}(u, A, s) \leq \mathcal{R}(u, A, s_0)$. Moreover, for any $\kappa \geq 1$, the set $\mathcal{C}^{RN}_{(u,A,\kappa)} = \{s|\mathcal{R}(u, A, s) = \kappa\}$ is connected.*

The key assumptions, as detailed in Appendix D, mean that increases in priority score will make the assignment probability of the safer college increase at a lower rate compared to the riskier one. As discussed in Appendix D, this statement is true for any pair of colleges whose cutoff distribution is log-concave[24] and of the same dispersion. The assumption is testable, and largely holds in our setting because we assume the cutoff distribution is normal and colleges of similar competitiveness have comparable dispersion of the cutoff distributions.

Similarly, define function $\mathcal{D}$ that maps preference profile u, priority score s, college A to its position κ on the list under the DC decision rule:

$$\mathcal{D} : (u, A, s) \mapsto \kappa$$

$\mathcal{D}$ is different from $\mathcal{R}$ in that a particular college need not move down the list as s increases. College A is not listed when s is too low, for similar reasons. As s increases, however, A first appears at the fourth choice once its probability is just high enough to exceed the previous fourth choice, which is the least appealing one on the list in terms of $p_A u_A$[25]. If u_A is higher than other listed colleges (despite lower probability, which results in lower $p_A u_A$ overall), A may move ***up*** as s increases, because p_A affects how A is ranked under the DC rule. A starts to move down gradually if s is so high that better colleges are within reach. Figure 4b presents an example where the position of a college evolves as priority score changes, where priority scores have been converted to admission probability of A on the horizontal axis. Compared to Figure 4a, it becomes apparent that the "climbing up to the top" movement to the left of the peak in Figure 4b distinguishes DC from the rational rule. The following theorem mathematically characterizes $\mathcal{D}$, when Assumptions 1, 2, 3, as detailed in Appendix D, hold:

Theorem 2 *Under Assumptions 1, 2, 3, for any preferences u and college A, if there exist $\underline{s}$ and $\bar{s}$ such that $\mathcal{D}(u, A, \underline{s}) = 0$ and $\mathcal{D}(u, A, \bar{s}) = \kappa$, then for any integer $\xi \in [1, \kappa]$, there exist $s \in [\underline{s}, \bar{s}]$ such that $\mathcal{D}(u, A, \bar{s}) = \xi$.*

The derivations of both theorems are detailed in Appendix D. Note that the assumption about the tie of expected utility is not essential, because, if we assume that students choose

[24]Log-concave distributions include normal distribution, uniform distribution, exponential distribution, logistic distribution, extreme value distribution, Pareto distribution, etc.

[25]For the sake of convenience, the outside option in this subsection is assumed to be 0.

randomly if more than two colleges tie, similar results emerge. When the assumption of both theorems hold, together they imply the following prediction:

Prediction 4 (Upward Movement) *In response to increase in priority scores, for any preferences, previously listed colleges will only move downward on the list under the rational decision rule, but may move upward under the DC decision rule.*

6.2 Variations in priority score that are orthogonal to preferences

Conditional on the same exam performance, the same academic ability leads to different provincial rankings of priority scores in different years. As discussed in Section 2, the college entrance exam consist of four subjects, and priority score is determined by summing up the *raw scores* of all subjects. However, the difficulty of subjects varies from year to year, such that the dispersion of students' performance does not move in the same direction, as demonstrated in Figure A6a. Given the unpredictability of subject difficulty, the way in which students' true academic ability is aggregated changes exogenously from year to year. For example, a student who is good at math may have a higher total score in a year where the math test is more difficult. To quantify the impact of such idiosyncratic aggregation, we regress rank-preserving score[26] on the polynomials of percentiles of each subject:

$$\text{Rank-Preserving Score}_i = f(Chinese\%_i, Math\%_i, English\%_i, Comprehensive\%_i) + \nu_i \quad (4)$$

If the regression is run within each year, the score should be mechanically predicted by the quantiles perfectly. If we run the regression over the whole sample (i.e., 2014-2018), quantiles cannot perfectly predict the score because of the cross-year change in score aggregation, as shown in Figure A6b. This regression thus decomposes the rank-preserving score into two orthogonal components, the predicted academic ability $\hat{f}_i$ and the residual $\hat{\nu}_i$. $\hat{\nu}_i$ is approximately normally distributed, creating additional variation whose standard deviation amounts to roughly 2 points in the priority score. While small, this creates enough variation for us to test the prediction in Section 6.1.

6.3 Testing Upward Movement in ROL: Data Analysis

For each student i and its selected college j, we divide the students according to the predicted probabilities in the absence of the score shock $\hat{\nu}_i$ (i.e., the probabilities converted from the

[26]Converting raw CEE score to its 2018 rank-preserving equivalent, as in Section 1.

predicted ability $\hat{f}_i$) into ten groups: 0.1% $\sim$ 10%, 10% $\sim$ 20%, 20% $\sim$ 30%, ... 80% $\sim$ 90%, 90% $\sim$ 99.9% and generate ten dummies. This set of variables is aimed at capturing any heterogeneity in preferences that are associated with students' academic ability. In other words, within each probability bin, students have essentially the same academic ability and thus any changes in preferences that are associated with academic ability have been controlled. Armed with the shock $\hat{\nu}_i$, we run the following random-coefficient regression to test our hypothesis:

$$y_{ij} = \beta_{(j,\text{SES Quarter},\text{Prob Bin})}\hat{f}_i + \gamma_{(j,\text{SES Quarter},\text{Prob Bin})}\hat{\nu}_i + FE_j * FE_{\text{SES Quarter}} * FE_{\text{Prob Bin}} + \epsilon_{ij} \tag{5}$$

where y_{ij} is the position of college j on student i's list (i.e., the vertical axis of Figure 4a and Figure 4b), FE_j is the college fixed effects, which aim to capture average preferences over college j non-parametrically, and $FE_{\text{SES Quarter}}$ is a dummy for the socioeconomic quartile that students belong to. The parameter of interest is the coefficient of score shock $\hat{\nu}_i$ (i.e., the "slope" of the movement in Figure 4a and Figure 4b) in each Prob Bin * SES Quarter * College cell, without imposing any restrictions across cells.

Under the assumption that students' preferences with regard to a specific college are homogeneous within each Prob Bin * SES Quarter * College cell, any positive estimates in $\gamma_{(j,SES)}$ that appear in any cluster would be interpreted as evidence of upward movement[27]. In other words, students who have similar socioeconomic status and academic ability, and choose to include the same college in their list (regardless of the position of the college), are assumed to have homogeneous (not necessarily vertical) preferences.

Figure 4c summarizes the distribution $\hat{\gamma}_{(j,SES)}$ by predicted admission probability in the absence of score shock. When the probability is lower than 20%, the mean of $\hat{\gamma}_{(j,SES)}$ is positive, suggesting substantial presence of the upward movement. When the predicted admission probability is above 20%, the estimated mean is around zero or negative. This does not indicate absence of the DC Type, because the movement among the DC Type is predicted to become downward when the probability is higher (Figure 4b). Moreover, the heterogeneity in $\hat{\gamma}_{(j,SES)}$ across college*SES cluster is not negligible even when the mean estimate of $\hat{\gamma}_{(j,SES)}$ is non negative. This finding also points to the massive presence of upward movement for higher probability bins. The numeric value of the aforementioned statistics are reported in Table B5.

[27] y_{ij} takes the value of 4, 3, 2, 1 if college j is listed as the first, second, third, and fourth choice respectively.

7 Structural Estimation using Administrative Data

7.1 Prediction of the DC Rule & Intuition of Identification

Because we are relying on risk-taking behavior to separate the DC Type from the Rational Type, once heterogeneous and horizontal preferences are incorporated into the model, it becomes less obvious how a structural model can identify the DC Type. The variation we are going to exploit is the variation in priority scores. As discussed in Section 6.2, conditional on the same academic ability, the cross-year variation in ranking and the resulting probabilities are arguably orthogonal to preferences.

How does this variation contribute to identification? A higher priority score increases the assignment probability of all colleges, *at different rates*. As discussed in Agarwal and Somaini (2018), with sufficient variation in assignment probabilities, it becomes possible to identify the distribution of preferences. While we are **not** claiming that the variation we have here is sufficient to identify arbitrary distribution of preferences, it is at least powerful enough to help identify the intensity of preferences, as well as the presence of the DC Type, as illustrated in the simplistic setting below.

Example There are four colleges, $A1$, $A2$, $B1$, $B2$. Let s denote priority score. $A1$ and $A2$ are risky (but potentially more desirable) colleges. Both of them have unconditional assignment probability $p_A(s)$ and admission utility $\delta > 0$. $B1$ and $B2$ are safe colleges. Both of them have unconditional assignment probability $p_B(s) > p_A(s)$; they have admission utility of 2 and 1 respectively. All the probabilities are independent. Students need to select two colleges from the four under a constrained Deferred Acceptance Algorithm. The utility of the outside option is 0.

Identifying Preference Intensity from Score Variation: Binary Choice Suppose the second position must be left blank, and students must choose from $A1$ or $B1$. Then, they choose $A1$ if and only if

$$\delta p_A(s) > 2p_B(s) \iff \frac{p_A(s)}{p_B(s)} > \frac{2}{\delta} \tag{6}$$

Figure A5 shows an example where different s leads to different ratio $\frac{p_A(s)}{p_B(s)}$. When the distributions of cutoffs of the two colleges are normal, as hypothesized in our setting, the ratio of assignment probability of $A1$ to $B1$ will be increasing as the probabilities are increasing at different rates[28]. If we can observe an individual making choices given a different priority score s, we would expect her to switch from $B1$ to $A1$ at some point. The earlier she switches, the more she likes $A1$ over $B1$. Consequently, for a group of students, the rate at which students switch from $A1$ to $B1$ identifies the density of δ.

Identifying DC Type Using Joint Changes in ROL When students select only one college, by definition the DC Rule cannot be distinguished from the Rational Rule. With two choices in the list, however, this becomes possible. As we observe how both choices change in response to increasing s, optimality implies that both choices are changing. The changes are jointly restricted because both are responses to the same preferences, as summarized by δ.

There are four possible portfolio choices in this setting, $(A1, A2)$, $(A1, B1)$, $(B1, A1)$, $(B1, B2)$. $(A1, A2)$ features substantial risk-taking, which for convenience is labelled as "reckless". $(A1, B1)$ features differential risk-taking in different positions ("diversifying"). $(B1, A1)$ features safer options before risky ones ("reversal"). $(B1, B2)$ features minimal risk-taking ("cautious"). We have the following results that help separate the DC Type from the Rational Type as the probability ratio $\frac{p_A(s)}{p_B(s)}$ increases:

Proposition 1 *As s increases, only the DC Type switches from "cautious" to "reversal" when $\frac{p_A(s)}{p_B(s)} < \frac{1}{2}$, and only the DC Type switches from "reversal" to "reckless" when $\frac{1}{2} < \frac{p_A(s)}{p_B(s)} < 1$.*

Why cannot preference alone explain the switch to and away from "reversals"? The reason is that the probability ratio $\frac{p_A(s)}{p_B(s)}$, which is observable to us, contains information about the magnitude of δ. When the switch happens with low $\frac{p_A(s)}{p_B(s)}$, the switch implies that preference intensity toward $A1$ and $A2$, δ, is high. For the Rational Type, high δ rules out the possibility of a reversal. Moreover, the point at which the switch happens also reveals the preference intensity of the DC Type. The rate at which the list switch happens identifies the probability density of δ.

[28] As discussed in Appendix D, the ratio will be increasing for any log-concave distributions if the cutoffs of the two colleges have the same dispersion. This scenario is largely in line with our hypothesis that the cutoff distribution of any two colleges of similar calibre share a similar standard deviation. When the dispersion is different, the range of the ratio usually will be wider, though not necessarily increasing in s.

7.2 Setup

Structure of College Preferences We parameterize college preferences to implement the structural estimation. For individual i, the utility of admission to college j is

$$u_{ij} = f(\theta_i^C, C_{ij}, SES_i) + g(\theta_i^d, d_j, SES_i) + h(\theta_i^X, X_j, SES_i) + O_i + \epsilon_{ij} \tag{7}$$

where C_{ij} is the competitiveness of college j with respect to student i, and SES_i is the average educational attainment in student i's township of residence. As detailed in Appendix C, function $f(.)$ controls the curvature over college preferences and takes the form of the CRRA function, with the curvature parameter being θ_i^C[29]. θ_i^C is normally distributed with unknown variance, and the mean is allowed to vary across students of different SES levels. We normalize d_j as the distance between students' home and the location of the college. Note that subscript i is omitted. Since all but two first-tier colleges are located outside Ningxia, and are clustered in metropolitan areas far away, the distances barely differ for students living in different areas in Ningxia. Function $g(.)$ controls preferences for distance and is quadratic with parameter vector θ_i^d. θ_i^d is jointly normally distributed with an unknown diagonal variance matrix, and the mean is allowed to vary across students of different SES levels. $h(\theta_i^X, X_j, SES_i)$ controls the interaction between other college characteristics and students' socioeconomic status, with the interaction parameter θ_i^X permitted to be normally distributed, with unknown variance and SES-specific mean. O_i measures the desirability of first-tier colleges overall relative to outside options. $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$ is the individual-college specific shock to admission utility. Appendix C discusses all the details of the specification.

Mixture Model We estimate a mixture model where there are two types of students: DC and rational. In this mixture model, we assume that share of the DC Type among students is a function of the SES status of student i:

$$P(\text{DC Type}|\text{SES}_i) = \frac{exp(\gamma_0 + \gamma_1 * SES_i)}{1 + exp(\gamma_0 + \gamma_1 * SES_i)} \tag{8}$$

Admission Probability In the benchmark estimation, we use the estimated probability $\hat{p_{ij}}$, as in Section 3.2. Appendix C discusses the case where one wishes to rely on students' subjective beliefs in the survey experiment to conduct estimation.

[29]We ensure that C_{ij} is positive by taking the difference between itself and the minimally competitive college.

7.3 Estimation Strategy

Following Section 4, we focus on students whose priority score percentile belongs to the top 60%, because these students' choices are less constrained. We split our sample according to students' CEE score and conduct the estimation for 40% $\sim$ 60%, 60% $\sim$ 80%, 80% $\sim$ 100% separately because students at different levels of academic ability tend to choose colleges of different levels of competitiveness, as demonstrated in Figure A7.

We include moments such as the mean assignment probability of the first, second, third, and fourth choices, as well as the share of reversals to target the moments that are directly related to the predictions of the DC Model[30]. In this parameterized model, the moments on characteristics of the listed colleges (physical distance, as well as share choosing a specific type of college) jointly identify the distribution of choice over colleges, hence the horizontal preferences over observables. As discussed in Section 7.1, curvature over competitiveness can be identified by the mean of the assignment probability of a single choice. Other horizontal preferences are assumed to be idiosyncratic, and thus bounded by the competitiveness of the choice. Estimated values of the moments for students whose score belongs to the 40 $\sim$ 60, 60 $\sim$ 80, or 80 $\sim$ 100 percentile are reported in Table B11, B14, B17 respectively. The moments are constructed separately for four SES quartiles to examine whether the share of the DC Type is higher among the socioeconomically disadvantaged, compared to their counterparts.

We use the Simulated Method of Moments to estimate this model. We simulate each student's choices 50 times, and calculate the simulated moments by averaging across different rounds. The estimation minimizes the weighted distance between simulated moments $m(\theta)$ and data m_0:

$$min\ (m(\theta) - m_0)'W(m(\theta) - m_0)$$

The estimator achieves asymptotic normality, with an estimated variance of:

$$(\hat{G}'W\hat{G})^{-1}(\hat{G}'W(1 + \frac{1}{50})(\hat{\Omega}/N)W\hat{G})(\hat{G}'W\hat{G})^{-1}$$

where 50 corresponds to the number of simulated choices for each observation (Laibson et al., 2007; DellaVigna et al., 2016), $\hat{G} \equiv \frac{\partial m(\theta)'}{\partial \theta}$ and $\hat{\Omega} = Var(m(\hat{\theta}))$. In our estimation, to enhance the efficiency of estimation, W is selected to be the inverse of the covariance matrix.

[30] Maximum likelihood estimation using ROLs, as in Agarwal and Somaini (2018); Calsamiglia et al. (2020); Kapor et al. (2020), is relatively more difficult because the number of portfolios one could construct amounts to billions in our setting. However, it may still be possible to use MLE in a computationally feasible way, according to the techniques introduced in Larroucau and Rios (2018).

7.4 Estimation Results

Table 4 compares the performance of a model that only allows for the Rational Type to a mixture model that allows for both the Rational Type and the DC Type. While all models are over-identified and rejected, the mixture model decreases the distance by 42.0%, 69.1%, 53.3% for the 40% ∼ 60%, 60% ∼ 80%, 80% ∼ 100% subsamples, respectively. This improvement is substantial. The MMSC-BIC metric[31] (Andrews and Lu, 2001), an analogue of the Bayesian Information Criterion, favors the mixture model over the rational benchmark as well.

The estimated share of the DC Type is 53.1% (SE=0.61%), 45.1% (SE=0.54%), 55.1% (SE=0.55%) for 40% ∼ 60%, 60% ∼ 80%, 80% ∼ 100% subsamples, respectively. These estimates are interestingly close to the estimate we get from the online survey (48.7%, SE=1.8%). The estimates on the marginal effect of SES are negative, where 1 standard deviation of decrease in SES index is associated with a decrease of 3.71% (SE=0.57%), 3.68% (SE=0.56%), 6.02% (SE=0.55%) in the propensity of being a DC Type. This negative effect is slightly less than the estimated effect from the survey (7.3%, SE=1.7%).

The estimated curvature over competitiveness is mild and sometimes positive, ranging from -0.486 to 0.413 (ρ in the CRRA specification), with all standard errors below 0.1. In summary, the levels of estimated curvature in both models are consistent with anecdotal evidence on the perceived importance of competitiveness/cutoffs on college prestige.

Out-of-sample prediction of the mixture model is also substantially better than the one-type rational model[32]. As demonstrated in Panel B of Table 4, compared to the one-type rational model, the mixture model decreases the distance by 14.9%, 43.4%, and 47.2%, respectively, and fits much better in the moments that are related to our predictions about cautiousness and reversals.

The DC Model helps fit the key moments of the data. Figure 5 compares the overall data and fit from the one-type rational model and the mixture model, for average risk-taking (Figure 5a) and share of reversals with different thresholds (Figure 5b), respectively. While both the one-type rational model and mixture model generate substantial reversals by introducing heterogeneous preferences, the one-type model fails to explain the cautiousness in the first choices by a fairly large margin (20%), while it predicts extreme cautiousness (probability $>$ 99%) for the fourth choices, contrary to the data, in which the mean of

[31] The formula for this metric is $d - (m - p)ln(n)$, where d is the distance, m is the number of moments, p is the number of parameters, and n is the sample size. The criteria favor smaller values.

[32] The structural estimation only uses the data from 2015, 2017, and 2018, because we have access to township-level student addresses only in these years to measure SES in a more precise way. The measure of SES in 2014 and 2016 is county-level adult educational attainment, which is substantially less precise, and thus is left out of the estimation and used for out-of-sample testing.

probability is around 90% for the fourth choices.

Although our model does not directly fit the estimates on upward movement, Figure 5c shows that, consistent with our theory, the estimated upward movement coefficient γ obtained by running regression 5 on the simulated sample generated by the estimated mixture model, is uniformly higher compared to that generated by the rational one-type model.

7.5 Welfare

The monetary measurement of welfare is motivated by the analogy that students' priority scores (determined by their exam performance, not by their college demand or strategy) serve as their WTP for college education, and that the cutoffs of the colleges serve as the prices of such services. We treat students' priority scores as their "budget set", and measure the welfare change as the equivalent variation (EV) in terms of priority score. In other words, for each individual applicant, the EV is the amount of change in its priority score in the current equilibrium that results in the same change in expected utility had the score remain unchanged under the new equilibrium.

To compute the counterfactual, we follow Kapor et al. (2020) by simulating how everyone would react to others' lists in the following two scenarios: (I) The system switches to Boston Mechanism with four spots without changing its decision rule; (II) All applicants respond optimally under the current system. We thereby obtain the new lists, and then use the new lists to simulate the cutoffs, iterating until convergence.

De-Biasing Conventional wisdom suggests that the sophisticated usually take advantage of the naive in a market setting (Gabaix and Laibson, 2006; Pathak and Sönmez, 2008), such that de-biasing could be a zero-sum game. However, in empirical settings, the intensity of vertical preferences may differ, and acting strategically will help students communicate such intensity (Abdulkadiroğlu et al., 2011). We report our findings in Panel C of Table 4. De-biasing improves the welfare of the 3rd, 4th and 5th quintiles of the DC Type, which is equivalent to an improvement of 0.495, 0.253, and 0.082 of a standard deviation of the priority score in the old equilibrium. Interestingly, de-biasing also increases the welfare of the Rational Type whose priority scores belong to the 3rd and 4th quintiles by 0.368 and 0.217 of a standard deviation of the score, and decreases the welfare of those whose scores belong to the highest quintile by 0.080 of a standard deviation. Intuitively, this happens because, in the old equilibrium, there is a mismatch effect between the behavioral type with a higher score and the rational counterpart with a lower priority score. De-biasing eliminates this effect and benefits any rational type whose score is not among the highest.

Effect of De-Biasing on Outcome Gap in Terms of Selectivity We know from Section 4.3 that the most socioeconomically disadvantaged quartile ends up in less selective colleges. In the structural model, this gap is explained by other differences in college preferences, or the behavioral biases. We examine how the gap would change under the counterfactual scenario in which all students are acting optimally. As reported in Table B3, Panel B, the gap shrinks by at least 83.15%, implying that, rather than heterogeneous preferences, most of the gap is explained by the behavioral biases.

Alternative Mechanisms DAA without limits on the number of choices would remove the advantage of the Rational Type, but students would not be able to express their preference intensity through risk-taking (Abdulkadiroğlu et al., 2011). Panel C reports the welfare effects of switching to unlimited DAA, which decreases the welfare of the Rational Type in the 3rd, 4th, and 5th quintiles by 0.329, 0.725, and 0.045 s.d. of the score. It increases the welfare of the DC Type in the 3rd and 4th quintile by 0.231 and 0.447 s.d. of the score, but decreases the welfare of the DC in the 5th quintile by 0.155 s.d. of the score. Overall, DAA without a limit is not welfare-enhancing for the majority of the students. An important caveat is that such evaluation ignores the differential impact of mistaken beliefs across mechanisms (Kapor et al., 2020).

An alternative is the Boston Mechanism, which intuitively makes bias less costly because it weakens the Rational Type's advantage of using backup choices as "insurance" to act aggressively for their top choices. Our results suggest that the Boston mechanism leads to a decrease in welfare for students of both types, although the decrease for the DC Type is smaller than the decrease for the Rational Type. Together with the results from DAA with an unlimited list, our analysis provides empirical support for Chen and Kesten (2017, 2019)'s theoretical finding that the Chinese parallel mechanism, as a middle ground between the Boston and DAA mechanism, may be better than both in our context.

Inequality Figure 6 presents how de-biasing and mechanism switching affect students of different socioeconomic status. Switching to an unconstrained Deferred Acceptance Algorithm or a Boston mechanism decreases the average welfare of students of every socioeconomic status. In contrast, de-biasing increases the welfare of all socioeconomic levels, where the welfare increase for the most disadvantaged quartile is equivalent to 0.294 s.d. of the score, and the welfare increase for the most advantaged quartile is equivalent to 0.221 s.d. of the score.

8 Discussion

Alternative Considerations Several factors that have been documented in the literature may also affect students' decision making. Appendix C.2 discusses, using the survey data, that to what extent students' subjective beliefs deviate from the estimated probability we construct using administrative data, and how the elicited beliefs affect the results of structural estimation. The primary finding is that using subjective beliefs increase the estimated share of the DC Type because the beliefs reflect higher degree of top-choice cautiousness. Appendix E.3 discusses correlation in the event of admission across colleges and finds that it does not affect the accuracy of estimated admission probability. Appendix E.4 discusses to what extent consideration of major could affect decision making, and find that it has minimal impact on risk taking behavior.

Psychological Mechanism The Model of Directed Cognition can naturally fit all the empirical patterns that we highlight. In addition to the failure of backward induction and contingent reasoning, the DC Model captures the idea that decision-makers tend to ignore the "background" of a problem when making individual choices. This intuition is similar to the theoretical models that describe how variation in choice attributes affects their salience and in turn affects the decision weight placed on them (Bordalo et al., 2012; Kőszegi and Szeidl, 2013; Bordalo et al., 2021). For example, if each spot of the rank-order list is viewed as an attribute of the portfolio, decision-makers may underweight the colleges that are already included when selecting individual colleges for other blank spots.

An alternative consideration is that the sequence in which a rank-order list is processed implies that uncertainty is resolved in multiple stages, which is a compound lottery problem. The established association between ambiguity aversion and failure of reducing compound lottery (Halevy, 2007; Chew et al., 2017) suggests that the inability to cope with multistage uncertainty could be caused by either ambiguity or complexity aversion. Regardless of its welfare implications, the model of directed cognition can be viewed as the limit point of the recursive utility specification in this literature. However, the documented framing effect in the survey experiment suggests that this psychological mechanism cannot explain all the suboptimal choices in our setting, because the uncertainty in later stages has been effectively eliminated in the incentivized survey questions.

As our findings could be potentially generalized to other mechanisms and settings where risky choices are interrelated, an important question for future research is to what extent the aforementioned factors influence the descriptive power of the DC Model in other contexts.

Implications for School Choice Systems A large literature documents that disadvantaged students select worse schools in the presence of school choice (Hastings and Weinstein, 2008; Hoxby and Avery, 2012; Walters, 2018). Our analysis suggests a novel channel through which a specific cognitive bias exacerbates inequality in educational attainment. Contrary to the convention wisdom, the documented behavioral biases affect not only equity, but also efficiency. The results suggest that intervening against the biases under the current system outperforms alternative popular mechanisms. This finding depends on the students' preference profiles. Caution needs to be exercised when applying this insight to other contexts.

References

Abdulkadiroğlu, Atila, Yeon-Koo Che, and Yosuke Yasuda (2011) “Resolving conflicting preferences in school choice: The” boston mechanism” reconsidered,” *American Economic Review*, 101 (1), 399–410.

Agarwal, Nikhil and Paulo Somaini (2018) “Demand Analysis using Strategic Reports: An application to a school choice mechanism,” *Econometrica*, 86 (2), 391–444.

——— (2019) “Revealed Preference Analysis of School Choice Models,” *Annual Review of Economics*, 12.

Ajayi, Kehinde F (2013) “School choice and educational mobility: Lessons from secondary school applications in Ghana,” *Institute for Economic Development Working Paper*, 259.

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky (2019) “Regressive sin taxes, with an application to the optimal soda tax,” *The Quarterly Journal of Economics*, 134 (3), 1557–1626.

Andrews, Donald WK and Biao Lu (2001) “Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models,” *Journal of econometrics*, 101 (1), 123–164.

Arteaga, Felipe, Adam J Kapor, Christopher A Neilson, and Seth D Zimmerman (2021) “Smart matching platforms and heterogeneous beliefs in centralized school choice,”Technical report, National Bureau of Economic Research.

Artemov, Georgy, Yeon-Koo Che, and Yinghua He (2017) “Strategic ‘mistakes’: Implications for market design research,” *NBER Working Paper*.

Bhargava, Saurabh, George Loewenstein, and Justin Sydnor (2017) “Choose to lose: Health plan choices from a menu with dominated option,” *The Quarterly Journal of Economics*, 132 (3), 1319–1372.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2012) “Salience theory of choice under risk,” *The Quarterly journal of economics*, 127 (3), 1243–1285.

——— (2021) “Salience,”Technical report, National Bureau of Economic Research.

Calsamiglia, Caterina, Chao Fu, and Maia Güell (2020) “Structural estimation of a model of school choices: The Boston mechanism versus its alternatives,” *Journal of Political Economy*, 128 (2), 642–680.

Camerer, Colin F, Eric Johnson, Talia Rymon, and Sankar Sen (1993) “Cognition and framing in sequential bargaining for gains and losses,” *Frontiers of game theory*, 104, 27–47.

Campbell, John Y (2016) “Restoring rational choice: The challenge of consumer financial regulation,” *American Economic Review*, 106 (5), 1–30.

Chade, Hector and Lones Smith (2006) “Simultaneous search,” *Econometrica*, 74 (5), 1293–1307.

Chen, Yan and Onur Kesten (2017) “Chinese college admissions and school choice reforms: A theoretical analysis,” *Journal of Political Economy*, 125 (1), 99–139.

——— (2019) “Chinese college admissions and school choice reforms: An experimental study,” *Games and Economic Behavior*, 115, 83–100.

Chetty, Raj, John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan (2020) “Income segregation and intergenerational mobility across colleges in the United States,” *The Quarterly Journal of Economics*, 135 (3), 1567–1633.

Chew, Soo Hong, Bin Miao, and Songfa Zhong (2017) “Partial ambiguity,” *Econometrica*, 85 (4), 1239–1260.

De Haan, Monique, Pieter A Gautier, Hessel Oosterbeek, and Bas Van der Klaauw (2015) “The performance of school assignment mechanisms in practice.”

DellaVigna, Stefano (2018) “Structural behavioral economics,” in *Handbook of Behavioral Economics: Applications and Foundations 1*, 1, 613–723: Elsevier.

DellaVigna, Stefano, John A List, Ulrike Malmendier, and Gautam Rao (2016) “Voting to tell others,” *The Review of Economic Studies*, 84 (1), 143–181.

Dreyfuss, Bnaya, Ori Heffetz, and Matthew Rabin (2019) “Expectations-based loss aversion may help explain seemingly dominated choices in strategy-proof mechanisms,”Technical report, National Bureau of Economic Research.

Esponda, Ignacio and Emanuel Vespa (2016) “Contingent preferences and the sure-thing principle: Revisiting classic anomalies in the laboratory,”Technical report, working paper.

Gabaix, Xavier and David Laibson (2006) “Shrouded attributes, consumer myopia, and information suppression in competitive markets,” *The Quarterly Journal of Economics*, 121 (2), 505–540.

Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen Weinberg (2006) “Costly information acquisition: Experimental analysis of a boundedly rational model,” *American Economic Review*, 96 (4), 1043–1068.

Halevy, Yoram (2007) “Ellsberg revisited: An experimental study,” *Econometrica*, 75 (2), 503–536.

Hassidim, Avinatan, Assaf Romm, and Ran I Shorrer (2016) “” Strategic” Behavior in a Strategy-Proof Environment,” in *Proceedings of the 2016 ACM Conference on Economics and Computation*, 763–764.

Hastings, Justine S, Christopher A Neilson, and Seth D Zimmerman (2013) “Are some degrees worth more than others? Evidence from college admission cutoffs in Chile,”Technical report, National Bureau of Economic Research.

Hastings, Justine S and Jeffrey M Weinstein (2008) "Information, school choice, and academic achievement: Evidence from two experiments," *The Quarterly journal of economics*, 123 (4), 1373–1414.

He, Yinghua (2015) "Gaming the Boston school choice mechanism in Beijing."

Hoxby, Caroline M and Christopher Avery (2012) "The missing" one-offs": The hidden supply of high-achieving, low income students,"Technical report, National Bureau of Economic Research.

Jia, Ruixue and Hongbin Li (2016) "Access to elite education, wage premium, and social mobility: the truth and illusion of China's college entrance exam," *Stanford Center for International Development, Working Paper* (577).

Johnson, Eric J, Colin Camerer, Sankar Sen, and Talia Rymon (2002) "Detecting failures of backward induction: Monitoring information search in sequential bargaining," *Journal of Economic Theory*, 104 (1), 16–47.

Kapor, Adam J, Christopher A Neilson, and Seth D Zimmerman (2020) "Heterogeneous beliefs and school choice mechanisms," *American Economic Review*, 110 (5), 1274–1315.

Kőszegi, Botond and Adam Szeidl (2013) "A model of focusing in economic choice," *The Quarterly journal of economics*, 128 (1), 53–104.

Laibson, David, Andrea Repetto, and Jeremy Tobacman (2007) "Estimating discount functions with consumption choices over the lifecycle,"Technical report, National Bureau of Economic Research.

Larroucau, Tomás, Manuel Martínez, Christopher Neilson, and Ignacio Rios (2021) "Application Mistakes and Information frictions in College Admissions."

Larroucau, Tomás and Ignacio Rios (2018) "Do "short-list" students report truthfully? Strategic behavior in the Chilean college admissions problem," *Preprint, submitted September*, 1 (10.13140).

——— (2020) "Dynamic college admissions and the determinants of students' college retention,"Technical report, Technical Report 2020. and,"Do "Short-List" Students Report Truthfully.

Li, Hongbin, Lingsheng Meng, Kai Mu, and Shaoda Wang (2021) "English Language Requirement and Educational Inequality: Evidence of 16 Million College Applicants in China."

Li, Shengwu (2017) "Obviously strategy-proof mechanisms," *American Economic Review*, 107 (11), 3257–87.

Lucas, Adrienne M and Isaac M Mbiti (2012) "The determinants and consequences of school choice errors in Kenya," *American Economic Review*, 102 (3), 283–88.

Martínez-Marquina, Alejandro, Muriel Niederle, and Emanuel Vespa (2019) "Failures in Contingent Reasoning: The Role of Uncertainty," *American Economic Review*, 109 (10), 3437–74.

Pathak, Parag A and Tayfun Sönmez (2008) "Leveling the playing field: Sincere and sophisticated players in the Boston mechanism," *American Economic Review*, 98 (4), 1636–52.

Rabin, Matthew and Georg Weizsäcker (2009) "Narrow bracketing and dominated choices," *American Economic Review*, 99 (4), 1508–43.

Rees-Jones, Alex, Ran Shorrer, and Chloe J Tergiman (2020) "Correlation Neglect in Student-to-School Matching,"Technical report, National Bureau of Economic Research.

Rees-Jones, Alex and Samuel Skowronek (2018) "An experimental investigation of preference misrepresentation in the residency match," *Proceedings of the National Academy of Sciences*, 115 (45), 11471–11476.

Rees-Jones, Alex and Dmitry Taubinsky (2020) "Measuring "schmeduling"," *The Review of Economic Studies*, 87 (5), 2399–2438.

Shorrer, Ran I (2019) "Simultaneous search: Beyond independent successes," in *Proceedings of the 2019 ACM Conference on Economics and Computation*, 347–348.

Shorrer, Ran I and Sándor Sóvágó (2018) "Obvious mistakes in a strategically simple college admissions environment: Causes and consequences," *Available at SSRN 2993538.*

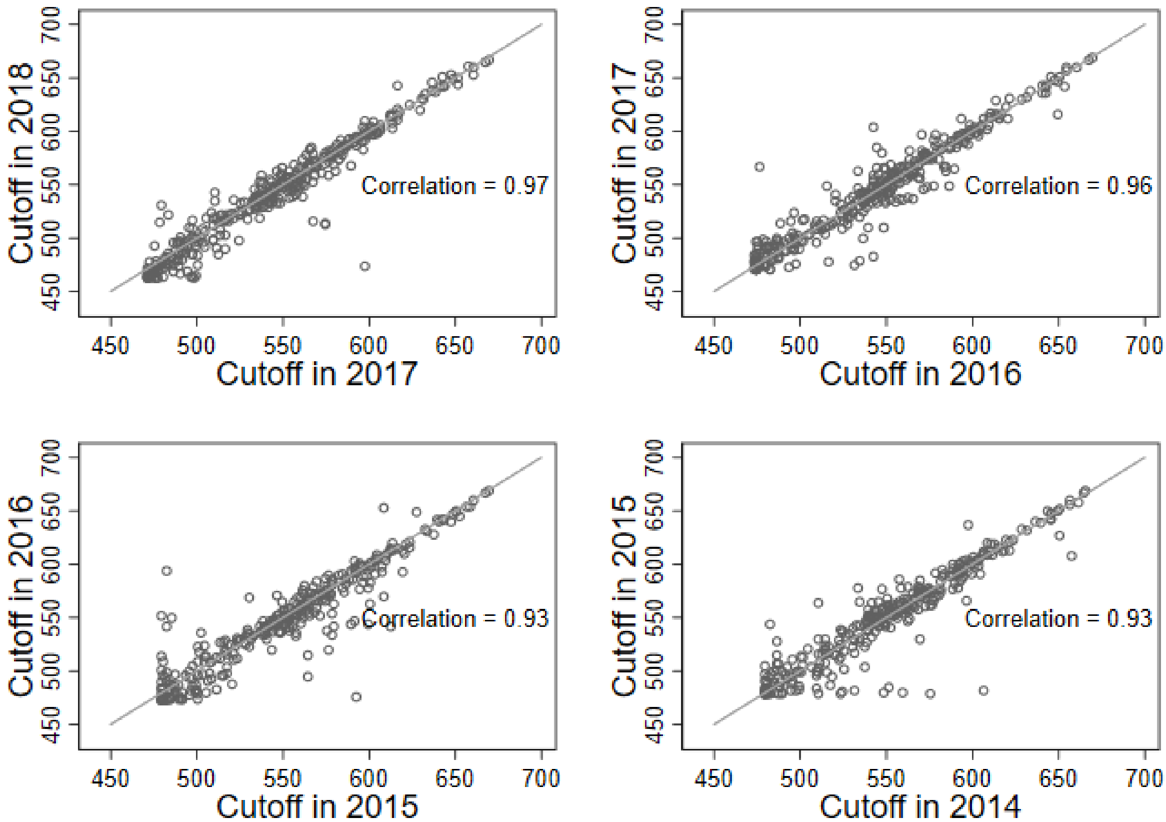
Song, Yan, Kentaro Tomoeda, and Xiaoyu Xia (2020) "Sophistication and Cautiousness in College Applications," *Available at SSRN 3711118.*

Sprenger, Charles (2015) "An endowment effect for risk: Experimental tests of stochastic reference points," *Journal of Political Economy*, 123 (6), 1456–1499.

Walters, Christopher R (2018) "The demand for effective charter schools," *Journal of Political Economy*, 126 (6), 2179–2223.

Wang, Ao, Shaoda Wang, and Xiaoyang Ye (2021) "Cognitive Distortions in Complex Decisions: Evidence from Centralized College Admission."

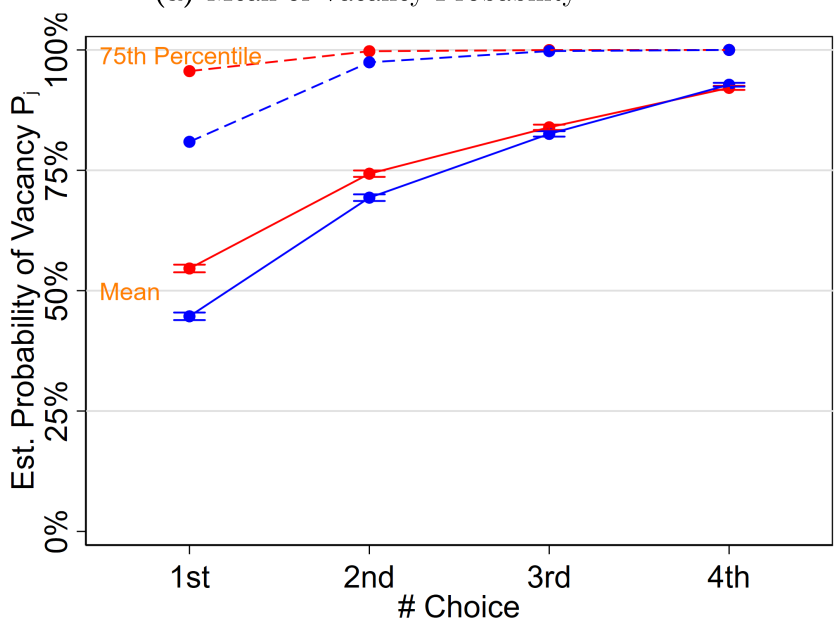
Figure 1: Admission Cutoffs Across Years



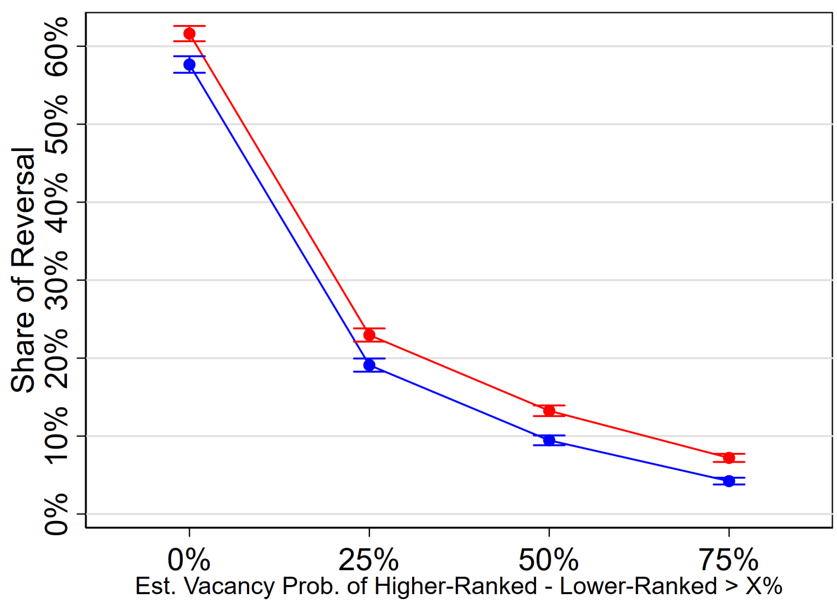
Note: This figure plots the admission cutoffs for all colleges that admit Ningxia students during 2014-2018, for the discussion in Section 3.2. The admission cutoffs are converted to its 2018 rank-preserving equivalents. Each dot represents the admission cutoffs of a specific college in two consecutive years. Top left graph plots the cutoffs in 2018 against 2017. Similarly, top right graph plots the cutoffs in 2017 against 2016; bottom left graph plots the cutoffs in 2016 against 2015; bottom right graph plots the cutoffs in 2015 against 2014.

Figure 2: Mean of Vacancy Probability and Share of Reversals by SES Groups

(a) Mean of Vacancy Probability



(b) Share of Competitive Reversals by Threshold X%



Note: This figure presents statistics for the most advantaged quartile (in blue) and the most disadvantaged quartile (in red), respectively. The sample is restricted to those whose priority score is top 60%, for the discussion in Section 4.3. Subfigure (a) plots the mean of vacancy probability (i.e. unconditional admission probability). Subfigure (b) plots the share of students whose strategy exhibits at least one pair of competitiveness reversals anywhere on her ROL, as a function of the threshold above which the reversal is counted in the statistic. The statistic we use to classify reversal is $R \equiv max\{p_i - p_j | \text{for any} 1 \leq j < i \leq 4\}$, only those whose R is above threshold $X\%$ will be counted. To maximize comparison, the mean from the least advantaged quartile has been reweighted to account for differences in priority scores.

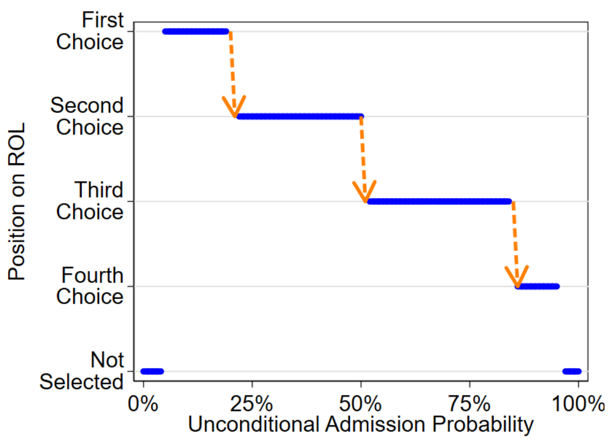
Figure 3: Distribution of Response to Incentivized Survey Questions

			Equivalent Lottery: Indifferent Between (25 CNY, 50%; 20 CNY, 50%) (L CNY, 25%; 20 CNY, 75%)		
			Very Cautious L≥50	Not Very Cautious L<50	Total
ROL 1st Choice:Payoff of non-first colleges is 20 CNY Indifferent Between (25 CNY, 50%) (R CNY, 25%)	Very Cautious	R≥50	72 5.1%	435 30.8%	507 35.9%
	Not Very Cautious	R<50	81 5.7%	824 58.4%	905 64.1%
	Total		153 10.8%	1259 89.2%	1412 100%

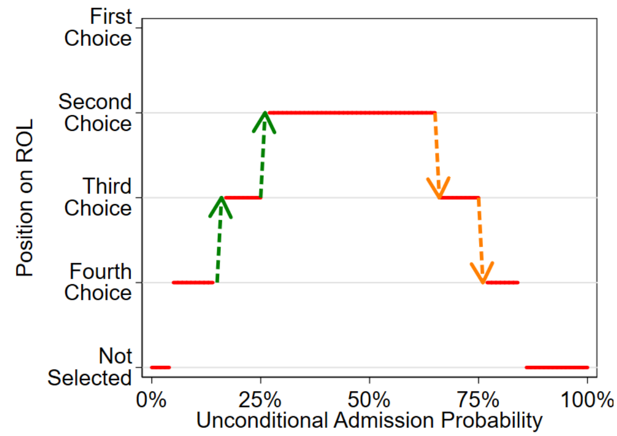
Note: This figure displays a coarsened joint distribution of responses to Question Group 1 (ROL 1st Choice) and Question Group 2 (Equivalent Lottery), for the discussion in Section 5.
Blue cells indicate that students' responses are both classified as "not very cautious" in the "ROL first-choice" problem and the equivalent lottery problem, as predicted by Rational Decision Rule.
Red cells indicate that students' responses are very cautious in "ROL first-choice" problem but not very cautious in the equivalent lottery problem as predicted by Directed Cognition (DC) Decision Rule.
Gray cells indicate that students' responses are not very cautious in "ROL first-choice" problem but very cautious in the equivalent lottery problem, which cannot be predicted by neither decision rule.
"ROL first-choice" question (vertical) corresponds to Question Group 1. In this question, students need to choose from college X, whose admission probability is 50% and payoff of admission is 25 CNY, or college Y, whose admission probability is 25% and payoff of admission is R CNY, where R = 30, 35, 40, 45, 50, 55, 60, respectively in the MPL, and put the college of their choice on the top of their list. If students are not admitted to their first choices, they will be admitted to one of the bottom choices in this scenario, which corresponds to the payoff of 20 CNY.
"Equivalent Lottery" question (horizontal) corresponds to Question Group 2. In this question, students need to choose from lottery X, whose payoff is 25 CNY with 50% of chance, 20 CNY with 50% of chance, or lottery Y, whose payoff is L CNY with 25% of chance, 20 CNY with 75% of chance, where L = 30, 35, 40, 45, 50, 55, 60, respectively. Note that "Equivalent Lottery Question" is mathematically equivalent to the aforementioned "ROL first-choice Question".

Figure 4: Prediction: Position Movement in ROL as Priority Score Changes

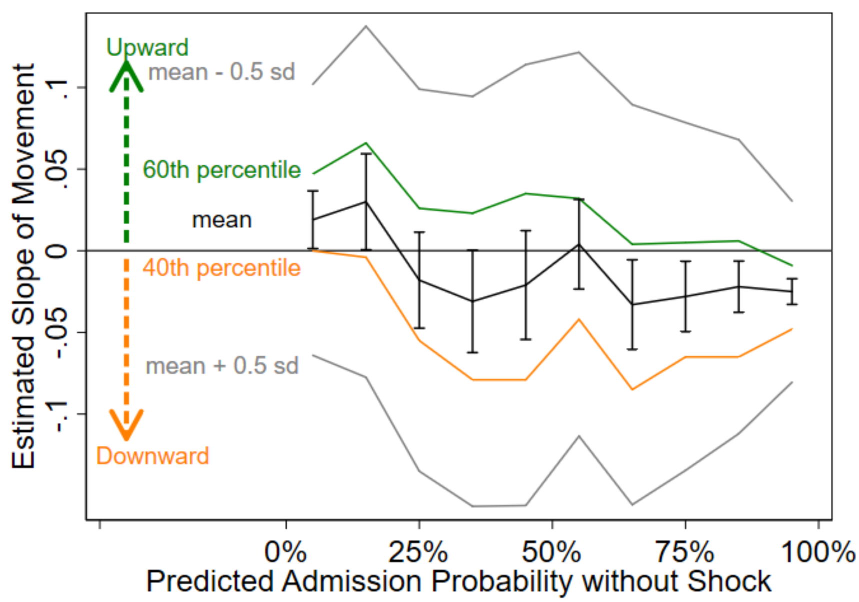
(a) Individual Choice Pattern under Rational Rule



(b) Individual Choice Pattern under DC Rule

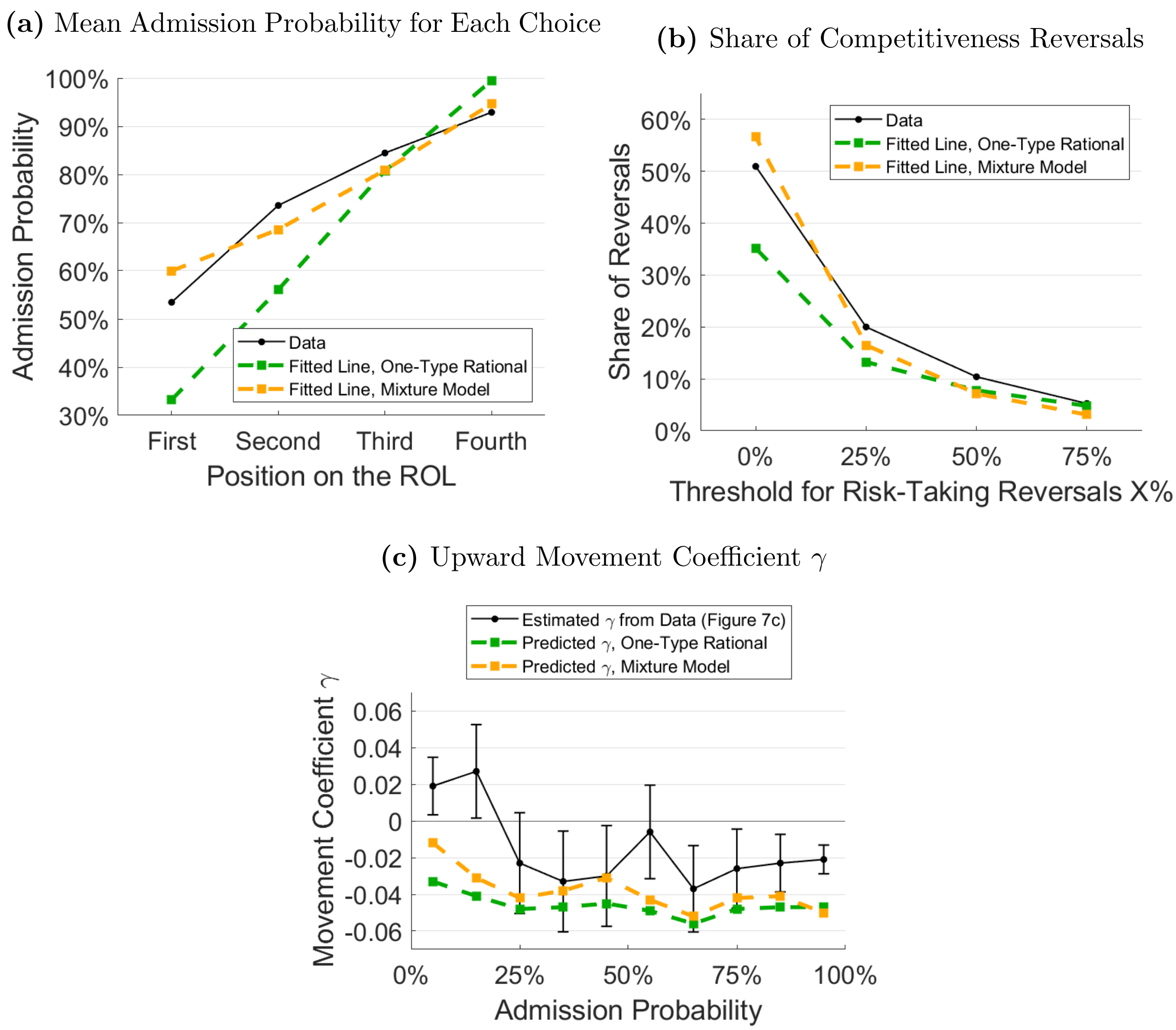


(c) Estimated Average Direction of Movement



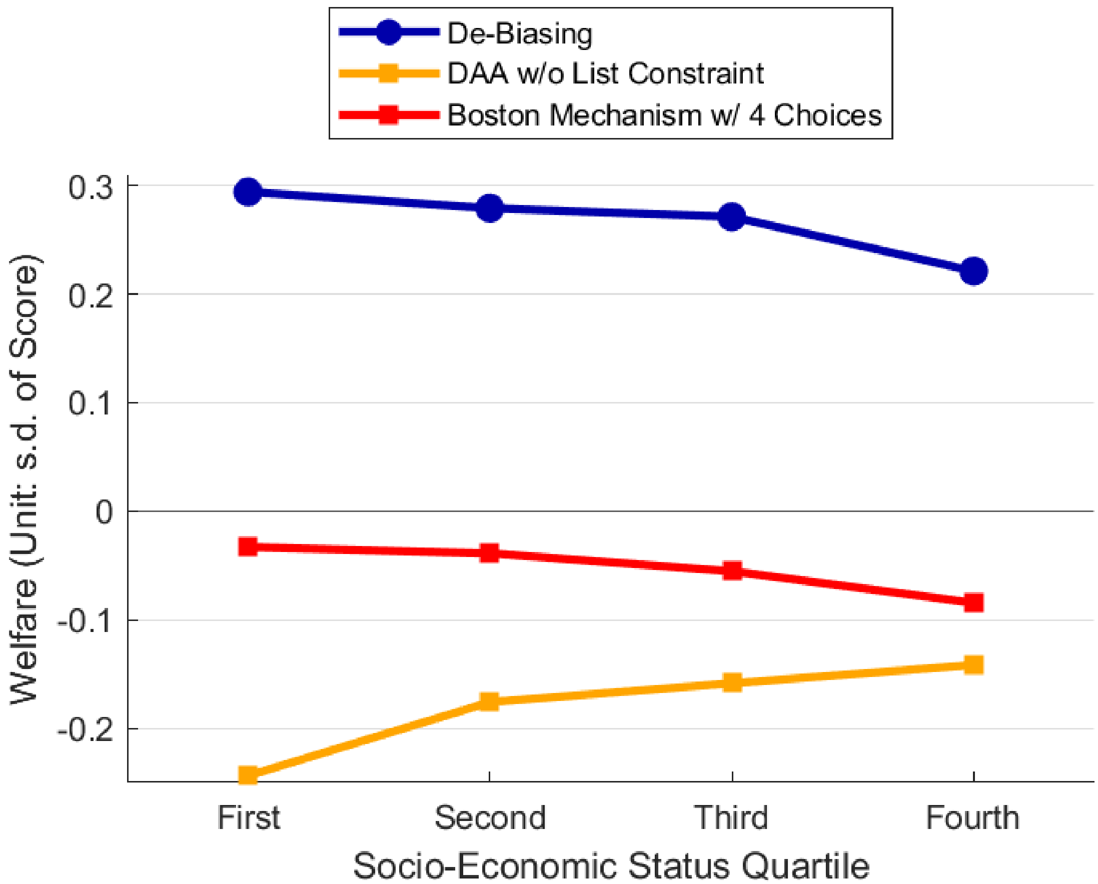
Note: This figure shows the prediction about how any single college move on the list as priority score changes under Rational Decision Rule and DC Decision Rule respectively, as discussed in Section 6.1, and 6.3. Subfigure (a) presents an example where the college in question is put on the list under Rational Decision Rule. Blue dots represent the position of the college given a level of priority score specified on horizontal axis. Subfigure (b) presents an example where the college in question is put on the list under DC Decision Rule. Red dots represent the position of the college given a level of priority score specified on horizontal axis. Subfigure (c) shows the estimated mean, 40th percentile, 60th percentile, mean ± 0.5sd of slope for each probability bin using the regression described in 6.3.

Figure 5: Data & Model Prediction: One-Type Rational vs. Mixture Model



Note: This figure compares the fit and data for the key moments in risk-taking strategies, as discussed in detail in Section 7.4. The fit is generated by the structural model that excludes students of the bottom 40% to minimize the impact of the constraint of priority score on college choices in the year of 2015, 2017, and 2018, where township level SES index can be obtained. Green dashed line is generated by the model that excludes the DC Type, but with the same degree of flexibility in preferences. Orange line is generated by our preferred model, the mixture model that allows for both Rational Type and the DC Type. Subfigure (a) plots the mean of unconditional admission probability for the first, second, third and fourth choices. Subfigure (b) plots the share of competitiveness reversals where the unconditional probability of the higher-ranked exceeds that of lower-ranked by more than X%. Subfigure (c) compares the estimated upward movement index, that is, the γ we obtain by running regression 5, from Figure 4c and Table B5. Table B12, B15, B18 report the fit of one-type rational model for all moments by the quintile of priority scores.Table B13, B16, B19 report the fit of one-type rational model for all moments by the quintile of priority scores.

Figure 6: Welfare Impact of De-Biasing and Alternative Mechanisms by SES Quartile



Note: This figure presents the mean of welfare impact of de-biasing, as well as switching to alternative mechanisms (Deferred Acceptance Algorithm without list constraints and Boston Mechanism with 4 choices), evaluated separately for students in each quartile of socioeconomic status index. The first quartile is the least advantaged. The fourth quartile is the most advantaged. The discussion of this figure is detailed in Section 7.5.

Table 1: Cautiousness of First and Fourth Choices:
Most Advantaged Quartile vs. Most Disadvantaged Quartile

Unconditional Admission Probability	(1) First	(2) Fourth	(3) Fourth-First
Panel A: Summary Statistics of Admission Probability			
Mean	45.96%	90.90%	44.94%
25th Percentile	6.93%	95.52%	9.04%
50th Percentile	41.32%	99.79%	47.09%
75th Percentile	84.30%	100.00%	83.46%
Panel B: Disadv-Adv Gap - Aggregate Estimate			
Most Disadvantaged Quartile	7.11%	-2.02%	-9.13%
	(0.67%)	(0.39%)	(0.75%)
Benchmark Group		Most Advantaged Quartile	
Predicted at Mean of Control: Most Advantaged	43.47%	91.95%	48.48%
	(0.41%)	(0.24%)	(0.46%)
4th-Order Polynomial of Priority Score	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Track (Science or Humanity) Fixed Effects	Yes	Yes	Yes
Panel C: Predicted Mean of Disadv-Adv Gap - by Quantile of Priority Score			
E[Adv-Disadv|Priority Score 40%]	6.59%	-1.36%	-7.95%
	(0.92%)	(0.53%)	(1.03%)
E[Adv-Disadv|Priority Score 60%]	8.22%	-1.91%	-10.14%
	(0.82%)	(0.48%)	(0.92%)
E[Adv-Disadv|Priority Score 80%]	10.47%	-2.09%	-12.56%
	(1.59%)	(0.92%)	(1.79%)
E[Adv-Disadv|Priority Score 99%]	6.13%	-1.64%	-7.77%
	(5.21%)	(3.01%)	(5.85%)

Note: This table reports reduced-form results from administrative data that analyzes the unconditional probability of students' first choices and fourth choices among students from the most disadvantaged quartile and the most advantaged quartile, as described in Section 4. Column 1 reports statistics related to the unconditional probability of the first choices. Column 2 reports statistics related to the unconditional probability of the fourth choices. Column 3 reports statistics related to the fourth-first choice gap, in terms of unconditional probability. Panel A reports the summary statistics of aforementioned variables. Statistics in Panel B and C are generated by a fixed effect regression that regresses outcome variables on the interaction of an indicator whether students belong to the most disadvantaged, and a fourth-order polynomial of priority scores. Panel B reports main effect of belonging to the most disadvantaged. Panel C examines the heterogeneity of adv-disadv gap by reporting the predicted mean of gap conditional on priority score quantile.

Table 2: Competitiveness Reversals:
Most Advantaged Quartile vs. Most Disadvantaged Quartile

	(1)	(2)	(3)	(4)
Threshold of Reversal X%: Probability of the Higher-Ranked Exceeds That of the Lower-Ranked by More Than X%	0%	25%	50%	75%
Panel A: Summary Statistics of Share of Risk Taking Reversal				
Mean	61.41%	23.74%	13.01%	6.70%
Panel B: Disadv-Adv Gap - Aggregate Estimate				
Most Disadvantaged Quartile	5.63%	6.79%	5.24%	3.96%
	(0.89%)	(0.77%)	(0.61%)	(0.45%)
Benchmark Group	Most Advantaged Quartile			
Predicted Share at Control Mean	59.26%	20.77%	10.58%	4.71%
	(0.55%)	(0.47%)	(0.37%)	(0.28%)
List of Controls				
4th-Order Polynomial of Priority Score	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Track (Science or Humanity) Fixed Effects	Yes	Yes	Yes	Yes
Panel C: Predicted Mean of Disadv-Adv Gap - by Quantile of Priority Score				
E[Adv-Disadv|Priority Score 40%]	6.82%	7.66%	6.47%	5.93%
	(1.22%)	(1.05%)	(0.83%)	(0.62%)
E[Adv-Disadv|Priority Score 60%]	5.32%	5.94%	4.41%	3.13%
	(1.09%)	(0.94%)	(0.75%)	(0.56%)
E[Adv-Disadv|Priority Score 80%]	4.51%	3.91%	2.17%	0.38%
	(2.12%)	(1.83%)	(1.44%)	(1.08%)
E[Adv-Disadv|Priority Score 99%]	8.80%	8.30%	4.78%	0.72%
	(6.91%)	(5.96%)	(4.72%)	(3.53%)

Note: This table reports reduced-form results from administrative data that analyzes the risk-taking reversal, namely, choosing rank a safer college higher, among students from the most disadvantaged quartile and the most advantaged quartile, as described in Section 4. We classify a pair of choices as risk-taking reversal if the gap in terms of admission probability exceeds X%, where X takes the value of 0, 25, 50, 75 in Columns 1, 2, 3, 4, respectively. Panel A reports the summary statistics of share of reversals. Statistics from Panel B and C are generated by a fixed effect regression that regresses outcome variables on the interaction of an indicator whether students belong to the most disadvantaged, and a fourth-order polynomial of priority scores. Panel B reports the main effect of belonging to the most disadvantaged. Panel C examines the heterogeneity of adv-disadv gap by reporting the predicted mean of gap conditional on priority score quantile.

Table 3: Testing Framing Effect - Incentivized Survey Responses

Panel A: Framing Effect and Socio-Economic Status			
	(1)	(2)	(3)
		Prob(Red Block)	
		Very Cautious in ROL But Not Very Cautious in Lottery	
SES Index Normalized	-4.8%	-4.9%	-4.3%
	(1.3%)	(1.6%)	(1.4%)
Control: Priority Score	Yes	Yes	Yes
Control: Demographic Variables	No	Yes	Yes
Control: College Preferences	No	No	Yes
Panel B: Estimated Share of Type from Survey Responses			
Share of Directed Cognition Type: Mean	0.0%	50.4%	50.4%
	-	(1.7%)	(1.7%)
Marginal Effect of Normalized SES	0.0%	-5.3%	-5.5%
	-	(1.8%)	(1.8%)
Share of Sincere Type	0.0%	0.0%	0.8%
	-	-	(0.6%)
Power Utility Curvature ρ	0.510	0.760	0.758
	(0.014)	(0.011)	(0.011)
Number of Parameters	6	9	10
Log Likelihood	-9100.574	-8781.778	-8780.909
Number of Observations	1412	1412	1412
Bayesian Information Criterion	18244.66	17628.83	17634.35
Panel C: Framing Effect and Elicited College Application Behavior			
	Not More Cautious in ROL than Lottery (Red Block)	More Cautious in ROL than Lottery (Blue / Gray Block)	Difference
List the 1st Choice If Only One Spot	27.6%	50.8%	23.2%
	(1.4%)	(2.4%)	(2.7%)
List Top Two Choices If Only Two Spots	27.3%	34.5%	7.2%
	(1.4%)	(2.3%)	(2.6%)
Subject Probability of Meeting the Cutoff of the 1st Choice	48.0%	56.6%	8.5%
	(0.9%)	(1.5%)	(1.7%)
Subject Probability of Meeting the Cutoff of the 4th Choice	72.5%	70.6%	-1.8%
	(1.0%)	(1.6%)	(1.9%)
Share of Reversal: Subjective Probability Higher Ranked - Lower Ranked > 25%	18.4%	23.2%	4.8%
	(1.2%)	(2.0%)	(2.3%)

Note: This table reports empirical analysis from incentivized survey response, as described in Section 5. Panel A analyzes to what extent the framing effect, that is, being very cautious in college choice problem than its lottery equivalent, is correlated with students' socioeconomic status and their priority scores, controlling for other variables elicited in the survey. Panel B jointly estimates students' propensity of being a Directed-Cognition Type and their CRRA risk preferences using different specifications. Column (1) excludes any behavioral type. Column (2) estimates a mixture model of the DC and the rational type. Column (3) estimates a model that additionally allows for sincere type. Panel C summarizes whether the average behavior in reported college choices among students who exhibit framing effect differ from those who do not.

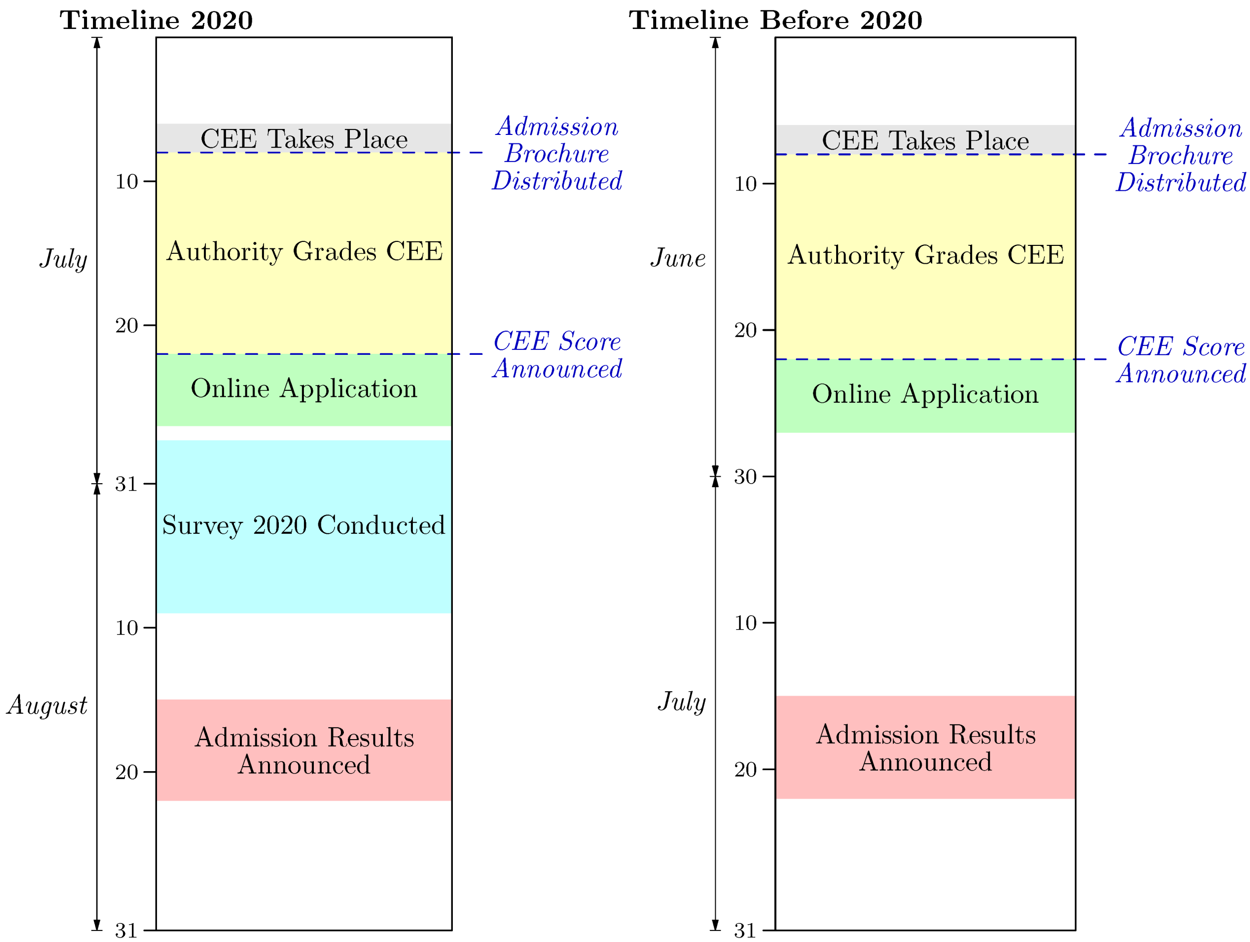
Table 4: Structural Estimation of Mixture Model using Administrative Data

Panel A: Estimation Results - Rational One-Type vs. Mixture Model	(1)	(2)	(3)	(4)	(5)	(6)
Sample (Quantile of Priority Score)	40%-60%		60%-80%		80%-100%	
Model	Rational	Mixture	Rational	Mixture	Rational	Mixture
Estimated Share of DC Type		53.1%		45.1%		55.1%
		(0.61%)		(0.54%)		(0.55%)
Marginal Effect of SES		-3.71%		-3.68%		-6.02%
		(0.57%)		(0.56%)		(0.55%)
Mean Curvature: Rational Type	-0.044	-0.375	0.413	-0.365	0.307	-0.336
	(0.007)	(0.027)	(0.022)	(0.024)	(0.014)	(0.021)
Mean Curvature: DC Type		-0.486		-0.459		-0.478
		(0.055)		(0.033)		(0.021)
Number of Moments	120	120	120	120	120	120
Number of Parameters	20	29	20	29	20	29
Distance	7699.344	4462.128	7008.675	2166.753	4737.862	2213.298
Decrease (Improvement) of Distance in Percentage	42.0%		69.1%		53.3%	
MMSC-BIC (Andrews&Lu, 2001)	6864.396	3702.324	6174.988	1408.098	3903.911	1454.404
Panel B: Out-of-Sample Predictions - Rational One-Type vs. Mixture Model						
Sample (Quantile of Priority Score)	40%-60%		60%-80%		80%-100%	
Model	Rational	Mixture	Rational	Mixture	Rational	Mixture
Distance	5760.837	4903.896	5477.374	3102.324	3947.603	2083.348
Decrease (Improvement) of Distance in Percentage	14.9%		43.4%		47.2%	
Key Moments						
Data: Mean Probability of 1st Choices	44.1%		45.6%		63.6%	
Prediction: Mean Probability of 1st Choices	29.0%	58.4%	32.3%	55.5%	38.5%	67.3%
Data: Mean Probability of 4th Choices	85.8%		87.8%		95.0%	
Prediction: Mean Probability of 4th Choices	99.8%	94.3%	99.3%	92.0%	99.4%	97.4%
Data: Share of Reversals	61.3%		58.0%		51.9%	
Prediction: Share of Reversals	33.0%	52.3%	37.1%	62.2%	36.1%	56.7%
Panel C: Welfare Evaluation Using Mixture Model (Unit: Standard Deviation of Priority Score)						
Sample (Quantile of Priority Score)	40%-60%		60%-80%		80%-100%	
Type	Rational	DC	Rational	DC	Rational	DC
Debiasing	0.368	0.495	0.217	0.253	-0.080	0.082
Deferred Acceptance with Unrestricted List	-0.329	0.231	-0.725	0.447	-0.045	-0.155
Boston Mechanism with 4 Choices	-0.147	-0.066	-0.074	-0.021	-0.152	-0.053

Note: This table reports the results of structural analysis as described in Sections 7.4 and 7.5, for the 40% $\sim$ 60% (column 1,2), 60% $\sim$ 80% (column 3,4), and 80% $\sim$ 100% (column 5,6) subsample. Columns 2,4,6 report estimation of mixture model where DC and Rational Type coexist. Columns 1,3,5 report estimation results of a rational model with flexible structure in college preferences. Standard errors are in parentheses. MMSC-BIC is a model and moments selection criteria for GMM developed by Andrews and Lu (2001). It is analogous to Bayesian Information Criterion in the context of maximum likelihood estimation.

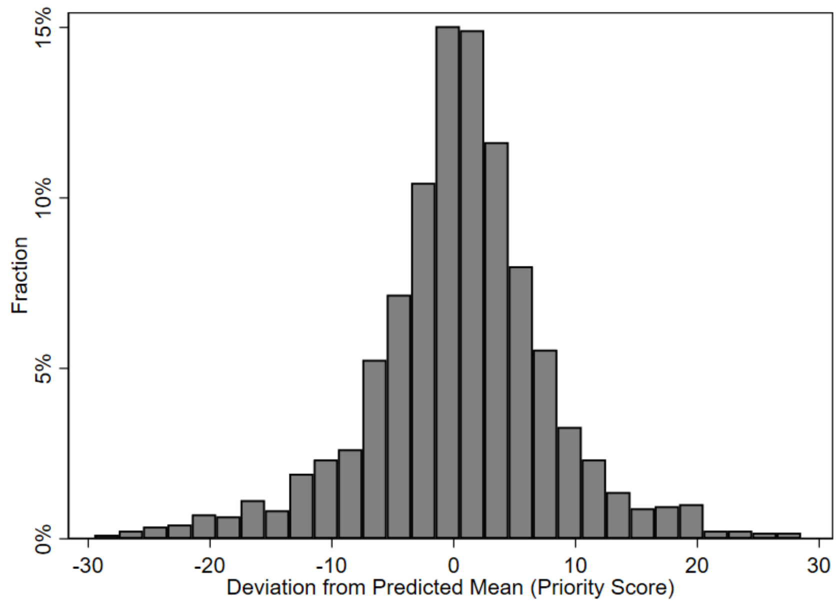
A Supplementary Figures

Figure A1: Timeline of College Admission Process

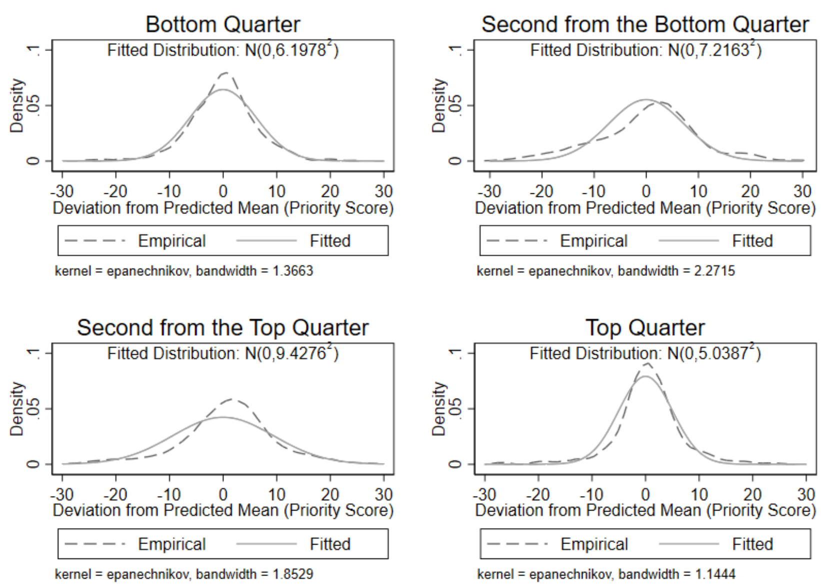


Note: This figure presents the timeline of college admission process, as detailed in Section 2. Note that the timeline remains unchanged until 2020, when the college entrance exam (CEE) was postponed by exactly one month due to COVID-19. As a result, all the admission procedures thereafter were postponed by exactly one month as well. As shown in the 2020 timeline, the survey was conducted right after application deadline, but before students were informed of their admission outcomes.

Figure A2: Distribution of Realized Cutoff-Predicted Mean Differences



(a) Distribution of Differences: All Colleges

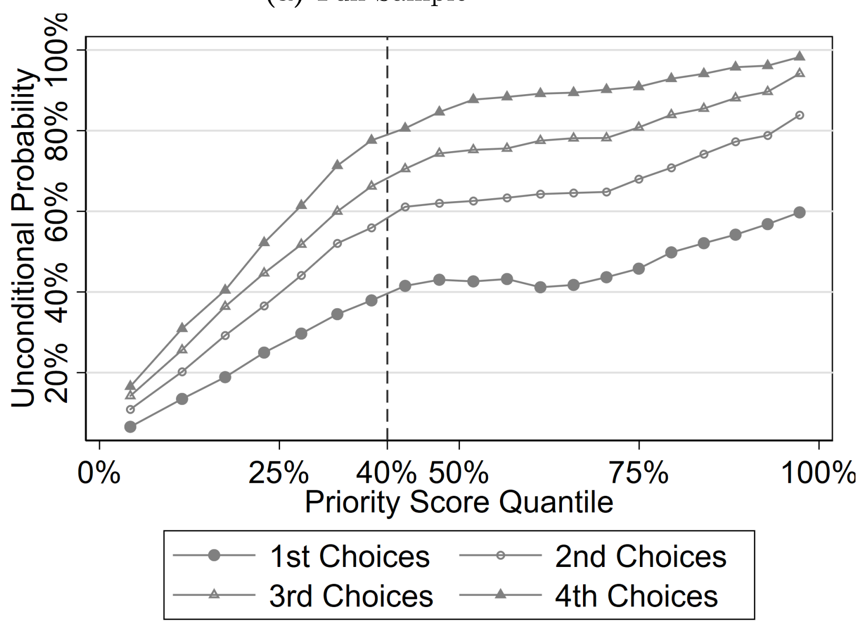


(b) Distribution of Differences by College Competitiveness

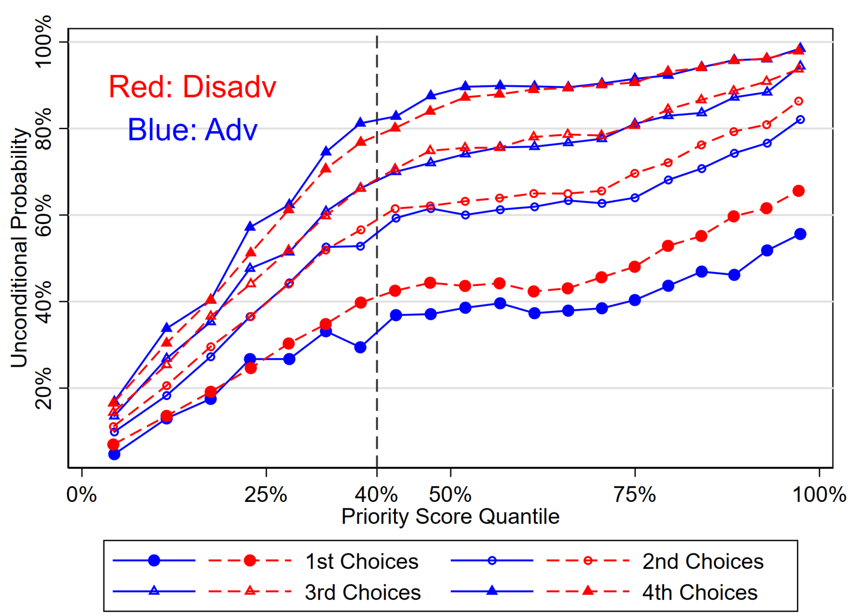
Note: This figure plots the distribution of distance between realized cutoffs and predicted mean as defined in Section 3.2. Subfigure (a) plots the distribution of differences between admission cutoffs and predicted mean among all colleges. Subfigure (b) plots the distribution of differences by college competitiveness, where the dashed lines in the top left, top right, bottom left, and bottom right graph are the empirical distribution for the least competitive quarter of colleges, second from the least competitive quarter, second from the most competitive quarter, and the most competitive quarter of colleges, respectively. The solid lines in subfigure (b) are fitted distributions using the median estimate of the standard deviation of cutoff-mean difference for corresponding quarter of colleges. Both subfigures omit outliers which is more than 30 points away from the predicted mean.

Figure A3: Mean of Admission Probability Conditional on Priority Score

(a) Full Sample

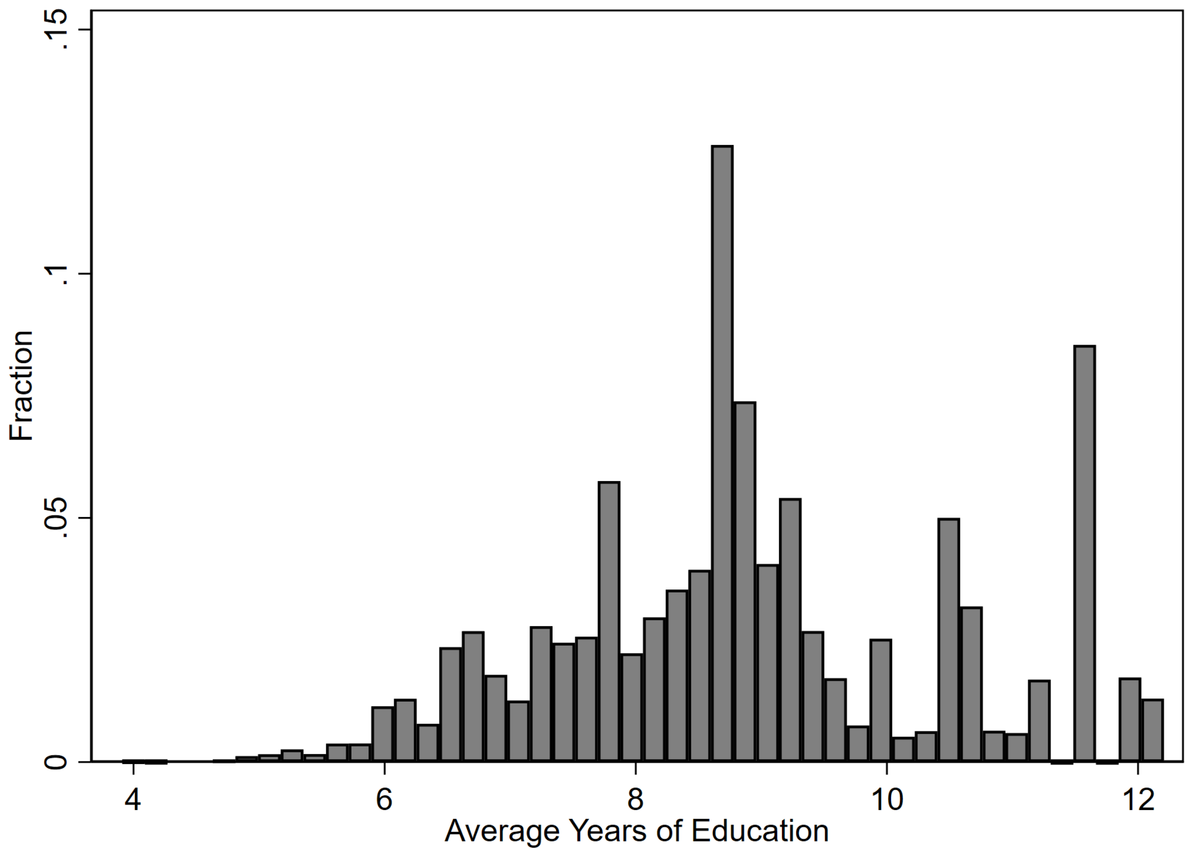


(b) Advantaged cs. Disadvantaged



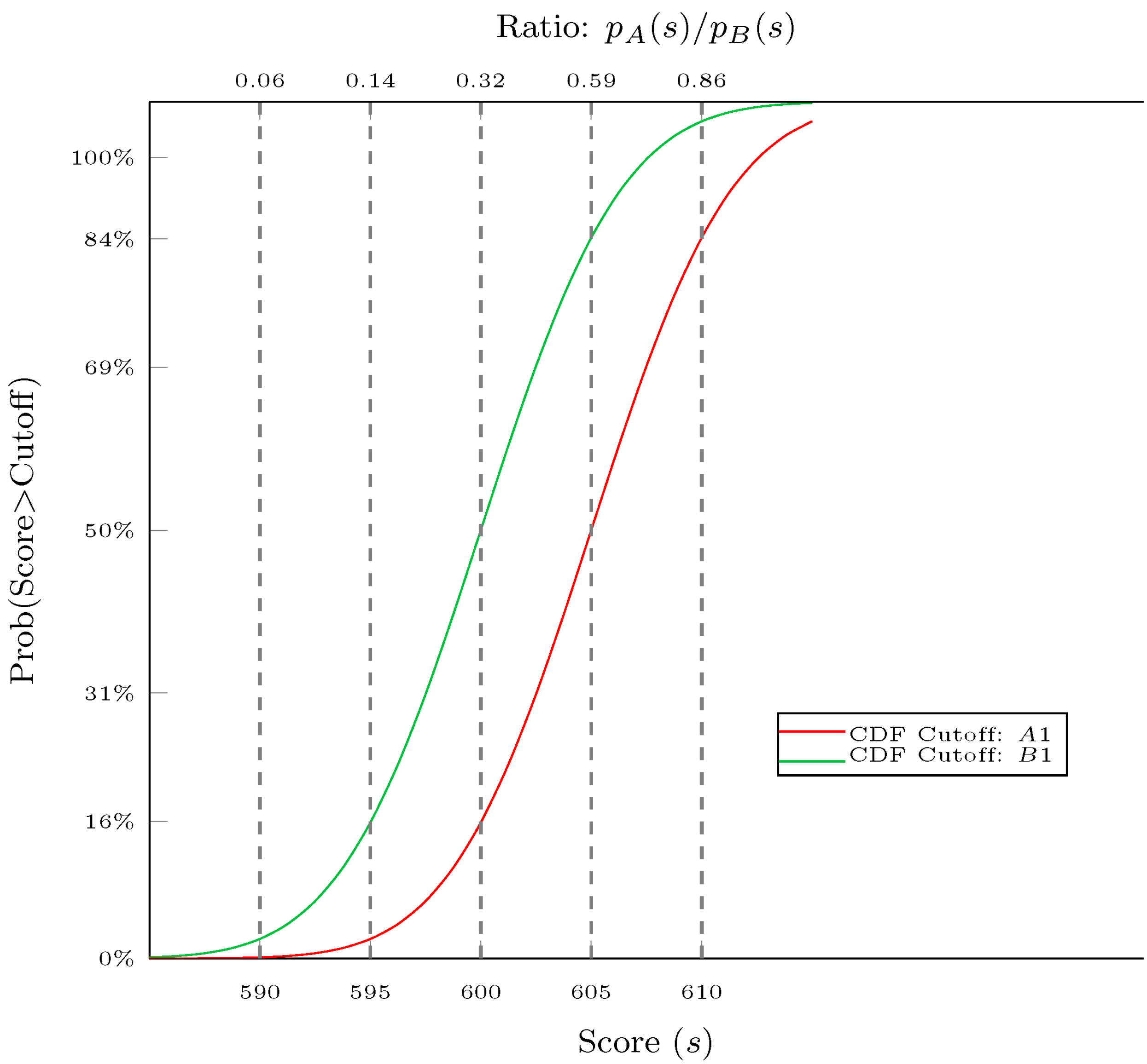
Note: This figure plots the mean of admission probability conditional on the quantile of priority score for student applicants' first choices, second choices, third choices and fourth choices, respectively. Subfigure (a) plots the statistics for the entire sample. Subfigure (b) plots the statistics for the advantaged students (the most advantaged quartile in terms of township-level education attainment) in blue, and for the other students in red. This graph is helpful for the discussion in Section 4.

Figure A4: Average Years of Education in Administrative Data (Township Level)



Note: This figure plots the cumulative distribution of probability of meeting cutoffs for students' first (in red), second (in yellow), third (in green) and fourth (in blue) choices, respectively, during 2014-2018. The figure demonstrates sizable heterogeneity in terms of educational attainment across different townships in Ningxia (25th percentile: 7.80 years; median: 8.73 years; 75th percentile: 9.88 years).

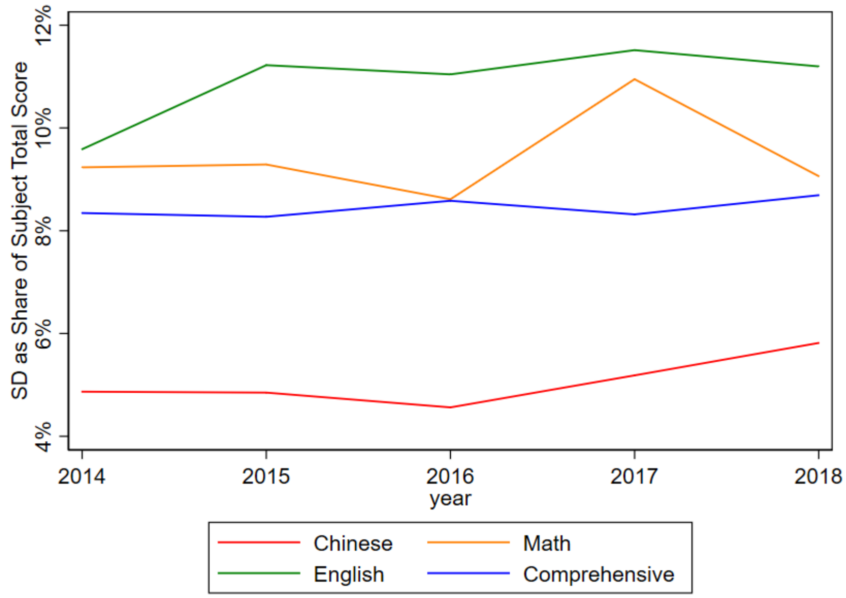
Figure A5: Example of Change in Priority Score Leading to Change in Ratio of Assignment Probability



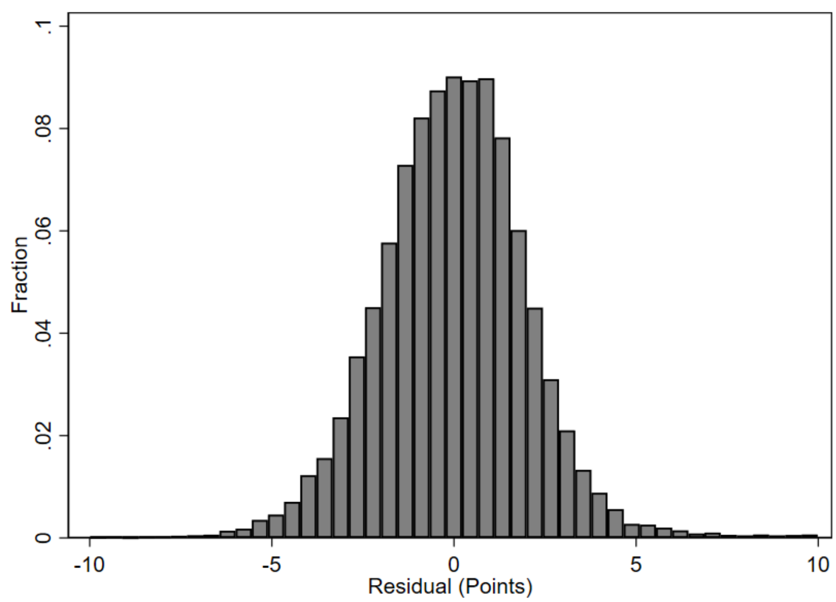
Note: This figure plots an example of the cumulative distributions of the cutoffs for two colleges, $A1$ and $B1$. Both distributions are normal distribution with standard deviation of 5, and the mean being 600 and 605 respectively. As shown in the upper horizontal axis, changes in priority scores lead to change in the ratio of assignment probability of $A1$ to $B1$. This graph is for the discussion in Section 7.1.

Figure A6: Impact of Subject Difficulty Variation on Admission Probability

(a) Difficulty of Subjects Varies Across Years

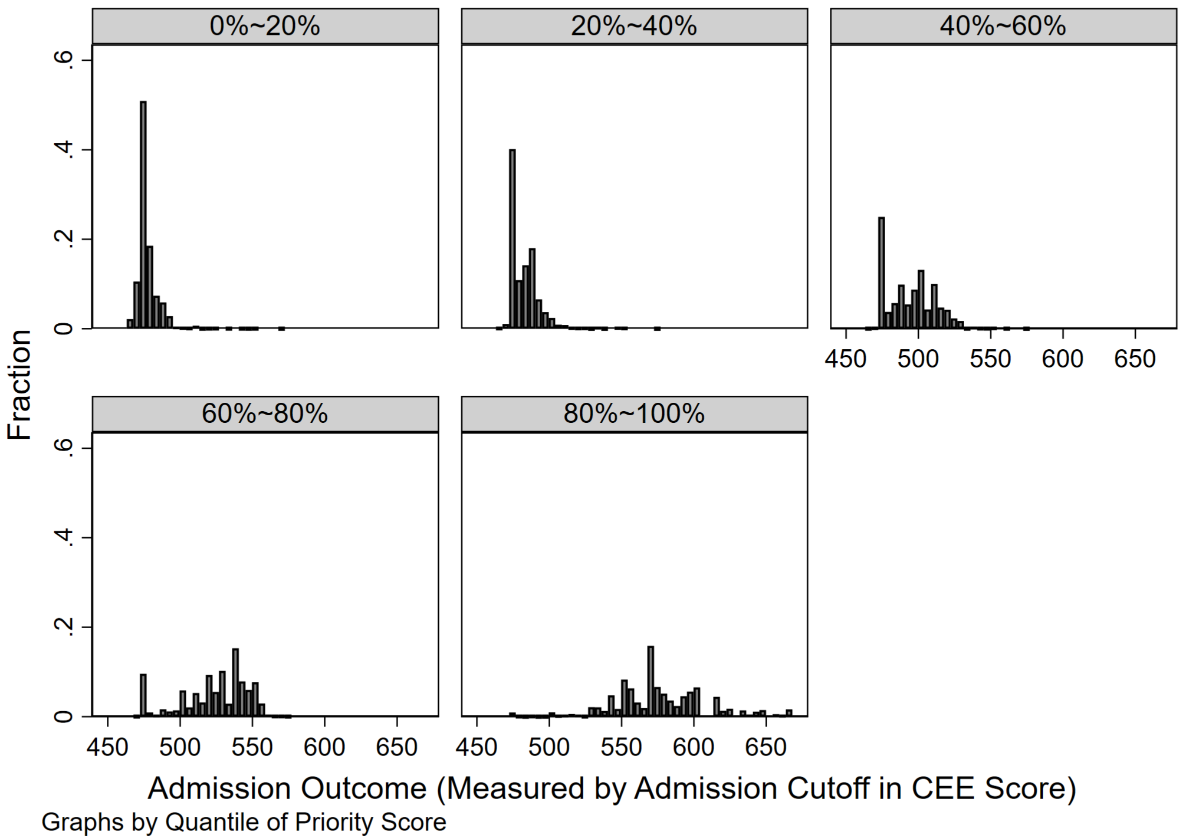


(b) Magnitude of Shock to Admission Probability is Sizable



Note: This figure explains the source of exogenous variation in admission probability. Subfigure (a) presents the standard deviation of raw exam scores as share of subject total scores for each subject during 2014-2018. Subfigure (b) is a histogram of the estimated distribution of shocks, rescaled in terms of the predicted standard deviation of cutoff of students' first choices. This graph is helpful for the discussion in Section 6.2.

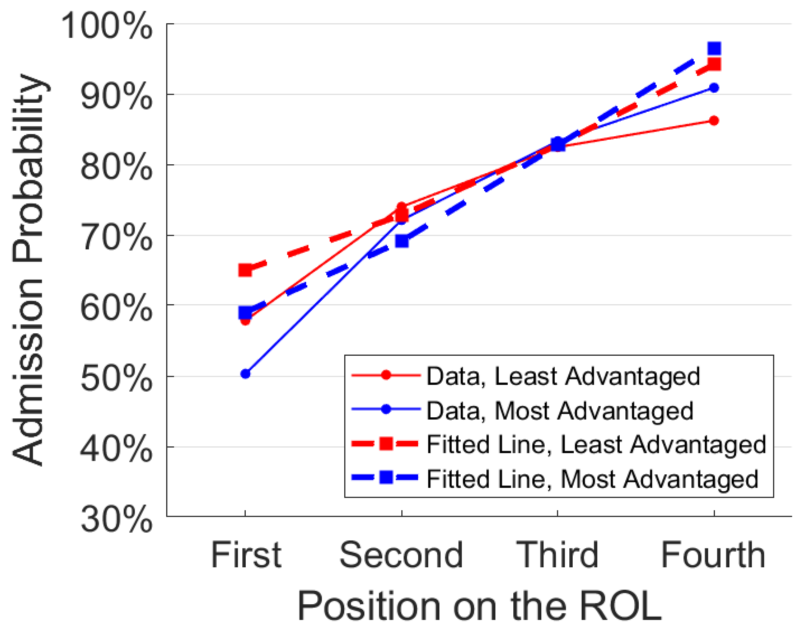
Figure A7: Competitiveness of Admitting College: by CEE Score Quantile



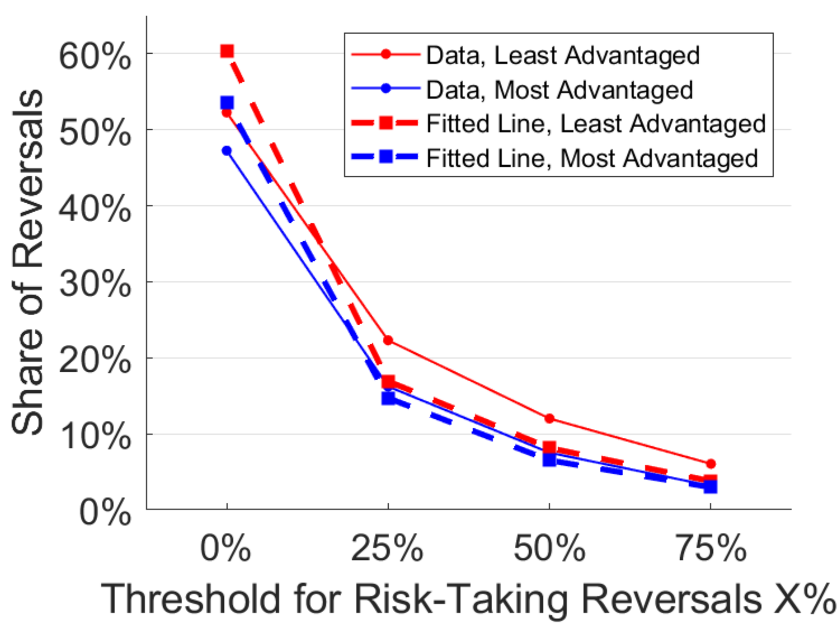
Note: This figure plots the distribution of colleges that admit students during 2014-2018. We split the entire sample of STEM applicants into five groups according to their CEE Score, with the first quintile being the group with lowest CEE Score and the fifth being the highest. This graph is helpful for the discussion in Section 7.

Figure A8: Data & Fit of Mixture Model: Advantaged vs. Disadvantaged

(a) Data vs. Fit: Mean Admission Probability for Each Choice



(b) Data vs. Fit: Share of Competitiveness Reversals



Note: This figure compares the fit and data for the key moments in risk-taking strategies, for the most advantaged quartile (4th quartile) and the least advantaged quartile (1st quartile) respectively, as discussed in detail in Section 7.4. The fit is generated by the structural model that excludes students of the bottom 40% to minimize the impact of the constraint of priority score on college choices in the year of 2015, 2017, and 2018, where township level SES index can be obtained. To maximize comparability across different SES groups, data have been reweighted to account for differences in priority score. Solid lines represent moments from data. Dashed lines represents values simulated by the estimated parameters from the mixture model. Blue lines represent the most advantaged quartile. Red lines represent the least advantaged quartile. Subfigure (a) plots the mean of unconditional admission probability for the first, second, third and fourth choices. Subfigure (b) plots the share of competitiveness reversals with different levels of threshold X%.

B Supplementary Tables

Table B1: Examples of Admission Rules

(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Admission Cutoffs				
Ex. Number	Priority Score	A	B	C	D	Admission Outcome
1	600	595	590	587	580	A
2	580	581	572	583	550	B
3	577	595	590	587	580	None
4	580	595	590	587	580	D

Note: This table presents four examples in which students with different priority scores applying for different sets of colleges in their ROLs. The serial number of examples is in Column (1). Each example is associated with a hypothetical student. The priority scores of the students are recorded in Column (2). Columns (3)-(6) present the admission cutoffs of the colleges that the students put in their ROLs. Column (7) presents the admission outcome of each hypothetical student as a result of their scores and ROLs. This table is helpful for the discussion in Section 2.2.

Table B2: Validity of Estimates of Unconditional Probability

	(1)	(2)	(3)	(4)
	Admitted to First		Admitted to Second	
Estimated Uncond. Prob. to First	0.9997	0.9954		
	(0.0043)	(0.0084)		
Estimated Uncond. Prob. to Second			0.9805	1.0033
			(0.0060)	(0.0110)
Constant	0.0056	0.0019	0.0183	-0.0002
	(0.0024)	(0.0041)	(0.0037)	(0.0062)
Subsample (Science/Humanity)	Science	Humanity	Science	Humanity
Empirical Share of Admitted	.4161	.3269	.4903	.4341
Predicted Share of Admitted	.3994	.2998	.4703	.4003

Note: This table reports the empirical exercise that tests the validity of probability estimates that we construct in Section 3.2. Columns 1 and 2 present the results of the regression where we regress the outcome of being admitted to the first choices on the estimated probability of meeting the cutoff of first choices, using the full sample of science-track and humanity-track students, respectively. Columns 3 and 4 present the results of the regression where we regress the outcome of being admitted to the second choices on the estimated probability of meeting the cutoff of second choices using the subsample of students who are not admitted to their first choices, for science-track and humanity track, respectively. This table is helpful for the discussion in 3.2.

Table B3: Admission Outcome and Score-Cutoff Gap

Panel A: Regression Analysis Using Administrative Data			
	(1)	(2)	(3)
	Selectivity of Admission Outcome (Normalized)		
Most Disadvantaged Quartile	-0.1288***	-0.1061***	-0.0962***
	(0.0082)	(0.0126)	(0.0209)
Benchmark Group	Most Advantaged Quartile		
CEE Score	Yes	Yes	Yes
Demographic Variables	No	Yes	Yes
County Fixed Effects	No	No	Yes
Panel B: Regression Analysis Using Simulated Data after De-Biasing			
	(1)	(2)	(3)
	Selectivity of Admission Outcome (Normalized)		
Most Disadvantaged Quartile	-0.0217*	-0.0106	0.0001
	(0.0125)	(0.0142)	(0.0162)
Benchmark Group	Most Advantaged Quartile		
Decrease in Outcome Gap%	**83.15%**	**90.01%**	**100%**
CEE Score	Yes	Yes	Yes
Demographic Variables	No	Yes	Yes
County Fixed Effects	No	No	Yes

Note: Panel A compares the selectivity of admitting college, as measured by cutoffs during 2014-2018 (normalized), for the most advantaged quartile to the least advantaged quartiles, with different sets of controls in different columns. Only the most advantaged and most disadvantaged quartile are included in the regression. Students' CEE scores have been controlled in all columns. Demographic variables are added as controls for Columns 2,3. County Fixed Effects are controlled in Columns 3. Panel B conducts exactly the same analysis using simulated data that are generated by the estimated college preferences in a counterfactual scenario where all students have learned how to apply optimally. Standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. This table is helpful for the discussion in Section 4.3.

Table B4: Design of Incentivized Questions in Survey

	Panel A1: ROL for Question Group 1			Panel C1: ROL for Question Group 3		
	ROL #	Payoffs	Prob(Meeting Cutoffs)	ROL #	Payoffs	Prob(Meeting Cutoffs)
	1st	?	?	1st	?	?
	2nd	20 CNY	100%	2nd	5 CNY	100%
	3rd	20 CNY	100%	3rd	5 CNY	100%
	4th	20 CNY	100%	4th	5 CNY	100%

	Panel A2: MPL for Question Group 1		Panel C2: MPL for Question Group 3	
Question #	College X	College Y	College X	College Y
(1)	25 CNY, 50%	30 CNY, 25%	25 CNY, 50%	30 CNY, 25%
(2)	25 CNY, 50%	35 CNY, 25%	25 CNY, 50%	35 CNY, 25%
(3)	25 CNY, 50%	40 CNY, 25%	25 CNY, 50%	40 CNY, 25%
(4)	25 CNY, 50%	45 CNY, 25%	25 CNY, 50%	45 CNY, 25%
(5)	25 CNY, 50%	50 CNY, 25%	25 CNY, 50%	50 CNY, 25%
(6)	25 CNY, 50%	55 CNY, 25%	25 CNY, 50%	55 CNY, 25%
(7)	25 CNY, 50%	60 CNY, 25%	25 CNY, 50%	60 CNY, 25%

	Panel B: MPL for Question Series 2	
Question #	Choice X (Payoff, Prob)	Choice Y (Payoff, Prob)
(1)	(25 CNY, 50%; 20 CNY, 50%)	(30 CNY, 25%; 20 CNY, 75%)
(2)	(25 CNY, 50%; 20 CNY, 50%)	(35 CNY, 25%; 20 CNY, 75%)
(3)	(25 CNY, 50%; 20 CNY, 50%)	(40 CNY, 25%; 20 CNY, 75%)
(4)	(25 CNY, 50%; 20 CNY, 50%)	(45 CNY, 25%; 20 CNY, 75%)
(5)	(25 CNY, 50%; 20 CNY, 50%)	(50 CNY, 25%; 20 CNY, 75%)
(6)	(25 CNY, 50%; 20 CNY, 50%)	(55 CNY, 25%; 20 CNY, 75%)
(7)	(25 CNY, 50%; 20 CNY, 50%)	(60 CNY, 25%; 20 CNY, 75%)

Note: This table presents the content of the three groups of incentivized MPL questions. Panels A1 and C1 present the ROL for Question Groups 1 and 3, respectively. Names of colleges for the second, third, and fourth spot are replaced with safe colleges that students are familiar with. Panels A2 and C2 present the MPL for Question Groups 1 and 3, respectively. In both question groups, students need to select either College X or College Y from each row, and the selected college will be put at the first spot in the corresponding ROL. Panel B presents the MPL for Question Group 2. Similarly, students need to choose one from Lottery X and Y in each row. This table is helpful for the discussion in Section 5.2.

Table B5: Testing Upward Movement of College Positions on ROLs

Predicted Probability of College of Choice if No Score Shock	Estimated Mean Movement μ_γ	Estimated Standard Deviation of Movement σ_γ	# Obs	# Cluster
0%∼10%	0.019 (0.008)	0.143 (0.009)	4769	324
10%∼20%	0.027 (0.013)	0.193 (0.014)	2342	235
20%∼30%	-0.023 (0.014)	0.211 (0.015)	2173	234
30%∼40%	-0.033 (0.014)	0.222 (0.016)	2087	239
40%∼50%	-0.030 (0.014)	0.231 (0.016)	2263	248
50%∼60%	-0.006 (0.013)	0.208 (0.014)	2533	274
60%∼70%	-0.037 (0.012)	0.212 (0.012)	3156	313
70%∼80%	-0.026 (0.011)	0.197 (0.013)	4116	352
80%∼90%	-0.023 (0.008)	0.168 (0.009)	5772	435
90%∼100%	-0.021 (0.004)	0.103 (0.007)	14952	632

Note: This table reports the estimated mean (μ_γ) and standard deviation (σ_γ) of the estimated slope of score shock, $\hat{\gamma}_{(j,SES)}$. The table corresponds to the empirical analysis in Section 6.3. We split the sample into ten bins according to whether the predicted academic ability, converted to admission probability in the absence of score shock falls into the category of 0.1% $\sim$ 10%, 10% $\sim$ 20%, 20% $\sim$ 30%, ... , 80% $\sim$ 90%, 90% *sim* 99.9%, and exclude samples where the probability is lower than 0.1% or higher than 99.9%, so that the score shock cannot generate substantial variation in admission probabilities. In terms of socio-economic status, we split students into four groups as we do previous sections. We run the specification in 5 for each college*SES quarter*probability bin separately, excluding the cell where there are less than 5 observations. The outcome variable is the position of a college on students' lists, which takes the value of 4 if listed as the first choice, 3 if listed as the second choice, 2 if listed as the third choice, 4 if listed as the fourth choice. For cells belonging to the same probability bin, we report the point estimate of the mean of the estimated slope for the score shock $\hat{\gamma}_{(j,SES)}$ and its standard error (Column 2), estimated standard deviation and of the estimated slope for the score shock $\hat{\gamma}_{(j,SES)}$ and its standard error (Column 3), number of college-student pair for each subsample (Column 4), number of clusters (coefficient of the score shock allowed vary across clusters) within each subsample (Column 5), where the score shock is defined as in Section 6.2. Point estimates for mean, standard deviation and their standard errors for each probability bin are calculated using bootstrap, with the replacement draw at the level of cells, weighted by the size of cell.

Table B6: Subjective Beliefs

	(1)	(2)	(3)	(4)
	Belief-Est. Prob.		| Belief-Est. Prob.|	
SES Index (Normalized)	1.00%	1.85%	1.08%	1.12%
	(0.51%)	(0.64%)	(0.36%)	(0.45%)
Mean	12.1%		31.0%	
Priority Score	Yes	Yes	Yes	Yes
Demographic Variables	No	Yes	No	Yes
College Preferences	No	Yes	No	Yes

Note: This table presents analysis of student applicants' subjective beliefs about the unconditional admission probability for relevant colleges. All columns present regressions that examine whether subjective beliefs differ systematically from estimated admission probability, and whether such difference is correlated with SES Index. The outcome variable in Columns 1 and 2 is the difference between subjective beliefs and estimated admission probability. Columns 3 and 4 are the absolute difference between subjective beliefs and estimated admission probability. The mean of bias and absolute biases have been calculated below the coefficient estimates. Besides SES Index, the only additional covariate in Columns 1 and 3 is the fourth-order polynomial of priority score, whereas in Columns 2 and 4 we additionally control for demographics and stated college preferences. This table is helpful for the discussion in Section C.2.

Table B7: Full Set of Parameter Estimates for Benchmark Model

	(1)	(2)	(3)	(4)	(5)	(6)
Sample (Quantile of Priority Score)	40%-60%		60%-80%		80%-100%	
Model	Rational	Mixture	Rational	Mixture	Rational	Mixture
γ_0		0.1252		-0.1973		0.208
		[0.0105]		[0.011]		[0.0148]
γ_1		-0.1498		-0.1493		-0.247
		[0.0105]		[0.0121]		[0.0159]
O^{RN}	201.2587	187.4907	111.921	176.7342	195.5955	8.7853
	[11.9669]	[33.1842]	[8.5226]	[32.3841]	[16.8046]	[2.2729]
O^{DC}		78.7562		-34.3799		44.9209
		[29.3449]		[1.9681]		[78.0733]
μ_C^{RN}	-0.0435	-0.375	0.4131	-0.3652	0.3066	-0.3359
	[0.0066]	[0.0355]	[0.0216]	[0.0241]	[0.014]	[0.0266]
ν_C^{RN}	-0.0776	0.0284	-0.1018	-0.0357	-0.1067	0.0066
	[0.0053]	[0.0095]	[0.0107]	[0.0105]	[0.0092]	[0.0086]
$\ln(\sigma_C^{RN})$	-4.1131	-1.062	-0.5165	-1.992	-4.3937	-4.9764
	[0.4797]	[0.0968]	[0.039]	[0.1842]	[0.7947]	[2.121]
μ_C^{DC}		-0.4856		-0.4591		-0.4782
		[0.0488]		[0.0268]		[0.024]
ν_C^{DC}		0.3762		-0.0812		-0.0187
		[0.0505]		[0.0112]		[0.0088]
$\ln(\sigma_C^{DC})$		0.448		-2.0757		-3.3633
		[0.0526]		[0.2075]		[0.5757]
μ_{d2}^{RN}	-6.8873	-9.992	-4.3441	0.1874	-3.6878	-4.9847
	[0.2233]	[0.5761]	[0.1344]	[0.1141]	[0.0849]	[0.4778]
ν_{d2}^{RN}	2.2877	-0.5175	-0.0243	0.1652	1.9706	1.1632
	[0.0969]	[0.2054]	[0.008]	[0.0751]	[0.0751]	[0.1969]
$\ln(\sigma_{d2}^{RN})$	1.9632	0.6009	0.2952	-0.8687	-2.4492	1.5638
	[0.0301]	[0.2898]	[0.0362]	[0.5457]	[0.5543]	[0.1205]
μ_{d2}^{DC}		-0.8002		1.0772		2.0291
		[0.1989]		[0.0987]		[0.1602]
ν_{d2}^{DC}		1.3624		1.0953		0.9078
		[0.2314]		[0.12]		[0.1419]
$\ln(\sigma_{d2}^{DC})$		1.953		1.5628		1.3889
		[0.0981]		[0.0886]		[0.1126]
$\ln(\sigma_\epsilon)$	-0.1207	2.6702	-0.9946	2.4079	-0.9616	-0.8188
	[0.0255]	[0.0821]	[0.1145]	[0.0821]	[0.0898]	[0.5159]
μ_{d1}	19.2221	11.789	19.7298	-6.0303	19.2848	-0.3039
	[0.8053]	[0.9965]	[0.6462]	[0.4852]	[0.4567]	[0.1945]
$\mu^{X,STEM}$	2.5861	0.2433	-1.0096	0.9482	-3.2708	-0.6504
	[0.1941]	[0.1266]	[0.2548]	[0.3918]	[0.8692]	[0.2704]
$\mu^{X,FIN}$	-2.5268	-1.4682	-0.8048	0.3164	-17.6289	-1.6289
	[0.578]	[0.9938]	[0.1611]	[0.3252]	[2.0334]	[0.6835]
$\mu^{X,MED}$	-1.2038	2.9692	-1.9315	-1.2749	-11.0285	-19.0556
	[0.2107]	[0.7749]	[0.3601]	[0.4728]	[2.1469]	[3.4944]
ν_{d1}	2.7649	0.9637	0.8853	1.5536	1.3512	2.8387
	[0.0326]	[0.263]	[0.1257]	[0.1478]	[0.0678]	[0.0951]
$\nu^{X,STEM}$	1.5886	2.9866	2.9986	2.9974	2.8672	1.9145
	[0.1374]	[0.147]	[0.1814]	[0.1647]	[0.1904]	[0.1866]
$\nu^{X,FIN}$	2.3696	2.8947	0.3958	2.0263	2.8453	2.4398
	[0.0645]	[0.1176]	[0.1496]	[0.1408]	[0.1074]	[0.1169]
$\nu^{X,MED}$	1.6335	-1.4377	1.4208	0.1856	2.2924	2.8106
	[0.0656]	[1.6394]	[0.1203]	[0.3431]	[0.1711]	[0.2065]
$\ln(\sigma_{d1})$	-3.1846	9.1148	2.7593	1.4381	-9.4213	1.1769
	[0.3308]	[0.9704]	[0.0745]	[0.3302]	[0.407]	[0.4923]
$\ln(\sigma^{X,STEM})$	0.8442	2.7324	1.3985	0.9126	-1.5138	-1.478
	[0.1108]	[0.3584]	[0.2833]	[0.3609]	[0.2493]	[0.3231]
$\ln(\sigma^{X,FIN})$	1.4157	1.5411	-0.1749	-1.1974	0.0788	-0.8185
	[0.2093]	[0.7664]	[0.0362]	[0.329]	[0.0437]	[0.4208]
$\ln(\sigma^{X,MED})$	-1.4415	-1.0368	-0.8789	-3.426	-2.1369	-6.5154
	[0.164]	[0.5986]	[0.1118]	[0.5875]	[0.3572]	[1.4997]

Note: This table presents the full set of parameter estimates for the benchmark model set up in Section 7.2 and detailed in Appendix D. Each column corresponds to the column with the same column number in Table 4, Panel A. Column 1 and 2 report the results of estimation that cover STEM students whose score is between 40% and 60% of the population. Column 3 and 4 report the results of estimation that cover STEM students whose score is between 60% and 80% of the population. Column 5 and 6 report the results of estimation that cover STEM students whose score is between 80% and 100% of the population. Odd columns report the results of the one-type rational model. Even columns report the results of the mixture model.

Table B8: Alternative Specifications of Structural Estimation

Panel A: Alternative Specifications - Less Flexible Preferences						
	(1)	(2)	(3)	(4)	(5)	(6)
Sample (Quantile of Priority Score)	40%-60%		60%-80%		80%-100%	
	Rational	Mixture	Rational	Mixture	Rational	Mixture
Estimated Share of DC Type		49.3%		47.8%		54.0%
		(0.25%)		(0.23%)		(0.30%)
Marginal Effect of SES		0.99%		-2.31%		-5.03%
		(0.33%)		(0.26%)		(0.31%)
Mean Curvature: Rational Type	-0.296	-0.312	-0.133	-0.500	0.259	-0.500
	(0.015)	(0.019)	(0.011)	(0.021)	(0.013)	(0.017)
Number of Moments	120	120	120	120	120	120
Number of Parameters	8	11	8	11	8	11
Distance	11647.42	4586.36	9181.853	4171.124	7247.197	3102.797
Decrease of Distance in Percentage	60.6%		54.6%		57.2%	
MMSC-BIC (Andrew&Lu, 2001)	10712.27	3676.267	8246.711	3261.031	6312.054	2192.703
Panel B: Alternative Specifications - Heterogeneous Beliefs						
Sample (Quantile of Priority Score)	40%-60%		60%-80%		80%-100%	
	Rational	Mixture	Rational	Mixture	Rational	Mixture
Estimated Share of DC Type		92.3%		96.2%		97.8%
		(0.51%)		(0.28%)		(0.26%)
Marginal Effect of SES		6.45%		-1.00%		-0.97%
		(0.48%)		(0.33%)		(0.40%)
Mean Curvature: Rational Type	-0.318	0.125	-0.100	4.529	0.090	10.445
	(0.016)	(0.045)	(0.011)	(1.171)	(0.005)	(9.113)
Mean Curvature: DC Type		-0.494		-0.478		-0.431
		(0.022)		(0.017)		(0.011)
Number of Moments	120	120	120	120	120	120
Number of Parameters	20	29	20	29	20	29
Distance	10026.09	4586.656	30492.2	4331.319	54968.45	3360.928
Decrease of Distance in Percentage	54.3%		85.8%		93.9%	
MMSC-BIC (Andrew&Lu, 2001)	9191.145	3826.853	29657.25	3571.516	54133.5	2601.125

Note: This table reports the results of structural analysis as described in Section 7.4 and C.2, for the $40\% \sim 60\%$ (column 1,2), $60\% \sim 80\%$ (column 3,4), and $80\% \sim 100\%$ (column 5,6) subsample using alternative specifications. Panel A reports the estimation results where the model is the same as the single-type/mixture model in Table 4 except that only preferences over competitiveness and distance is taken into account, and is homogeneous across types. Panel B reports the estimation results where the parameters are the same as in Table 4 but we additionally introduce perturbation in beliefs with the parameters of the perturbation distribution calibrated using data from the online survey.

Table B9: Full Set of Parameter Estimates for Model with Subjective Beliefs

	(1)	(2)	(3)	(4)	(5)	(6)
Sample (Quantile of Priority Score)	40%-60%		60%-80%		80%-100%	
Model	Rational	Mixture	Rational	Mixture	Rational	Mixture
γ_0		2.8421		3.2691		3.8864
		[0.0968]		[0.0704]		[0.0962]
γ_1		0.9663		-0.2743		-0.4509
		[0.0692]		[0.0798]		[0.144]
O^{RN}	47.6584	107.0377	186.5335	10.6943	180.4882	137.3104
	[1.21]	[43.6744]	[37.5617]	[8.8221]	[18.1934]	[117.3933]
O^{DC}		157.7041		190.9884		183.2862
		[13.5568]		[26.0062]		[10.4437]
μ_C^{RN}	-0.318	0.125	-0.0999	4.5286	0.0903	10.4447
	[0.0157]	[0.0452]	[0.0105]	[1.1712]	[0.0051]	[9.1129]
ν_C^{RN}	-0.3331	0.5939	0.0333	-2.0243	-0.0811	-2.6561
	[0.0165]	[0.0534]	[0.0023]	[0.7408]	[0.0032]	[5.2059]
$ln(\sigma_C^{RN})$	0.5627	-1.4185	-4.9141	-2.9601	-4.5224	0.969
	[0.0189]	[0.2319]	[0.4723]	[3.0393]	[0.2442]	[1.7258]
μ_C^{DC}		-0.4938		-0.4782		-0.4313
		[0.0217]		[0.0173]		[0.0113]
ν_C^{DC}		0.1451		0.0125		0.0859
		[0.0091]		[0.0048]		[0.0055]
$ln(\sigma_C^{DC})$		-1.4356		-1.7559		-2.4135
		[0.0855]		[0.0767]		[0.1239]
μ_{d2}^{RN}	-7.5468	-9.9297	-3.735	-2.4629	0.3301	-9.605
	[0.1596]	[1.2335]	[0.1393]	[0.5696]	[0.0176]	[3.4907]
ν_{d2}^{RN}	3.5104	9.9625	-0.0764	0.4132	2.8769	-7.116
	[0.0665]	[2.1119]	[0.0202]	[0.2359]	[0.0509]	[5.0562]
$ln(\sigma_{d2}^{RN})$	1.5154	1.4246	-1.7818	-0.8556	-0.1169	-3.3158
	[0.0456]	[0.3211]	[0.3147]	[0.9039]	[0.0103]	[8.6852]
μ_{d2}^{DC}		-3.2083		-2.1032		-1.5258
		[0.144]		[0.117]		[0.0829]
ν_{d2}^{DC}		-0.3515		1.0558		-2.7604
		[0.1002]		[0.1114]		[0.1335]
$ln(\sigma_{d2}^{DC})$		1.8952		1.9454		1.8639
		[0.0427]		[0.0518]		[0.0384]
$ln(\sigma_\epsilon)$	2.9464	-0.5798	1.8222	-0.0608	1.4472	-0.6756
	[0.0307]	[0.2055]	[0.0397]	[0.0425]	[0.0283]	[0.2144]
μ_{d1}	18.7384	3.1024	16.9153	-0.3039	-2.2612	2.2743
	[0.5076]	[0.4419]	[0.691]	[0.1461]	[0.0893]	[0.3412]
$\mu^{X,STEM}$	-5.1322	3.8767	2.0138	7.4614	8.0496	2.8957
	[0.3121]	[0.3017]	[0.0961]	[0.453]	[0.3364]	[0.1916]
$\mu^{X,FIN}$	-11.7332	-2.9445	-1.4988	0.6211	-3.7295	5.735
	[0.8499]	[0.5674]	[0.3792]	[0.381]	[0.4408]	[0.3263]
$\mu^{X,MED}$	7.1795	-1.0502	1.918	-1.6456	-7.5212	-14.348
	[0.5578]	[0.2793]	[0.1722]	[0.3956]	[0.6757]	[1.2808]
ν_{d1}	0.4596	-0.0773	2.7294	0.0399	0.5844	2.2082
	[0.073]	[0.0459]	[0.0269]	[0.0444]	[0.0516]	[0.1145]
$\nu^{X,STEM}$	2.7988	2.9991	1.752	2.9994	2.9885	-2.9022
	[0.1119]	[0.1172]	[0.1591]	[0.1179]	[0.0706]	[1.7772]
$\nu^{X,FIN}$	2.8043	2.65	1.5981	2.8016	2.9536	-2.1044
	[0.0681]	[0.0686]	[0.1113]	[0.0577]	[0.0369]	[1.4557]
$\nu^{X,MED}$	-0.6704	1.2725	-1.6872	1.7481	1.0976	2.4194
	[0.3478]	[0.1653]	[0.9522]	[0.1583]	[0.1879]	[0.1209]
$ln(\sigma_{d1})$	-8.0958	6.2332	4.8218	2.5848	-14.3383	19.9639
	[0.2669]	[0.4444]	[0.1587]	[0.5162]	[0.2752]	[0.6979]
$ln(\sigma^{X,STEM})$	-0.3587	-1.2404	0.4852	1.9126	5.6399	-3.3723
	[0.1268]	[0.2316]	[0.0968]	[0.2988]	[0.2929]	[0.2044]
$ln(\sigma^{X,FIN})$	-2.7558	-4.93	-1.3575	-1.1153	7.3209	-5.1778
	[0.4987]	[0.4187]	[0.1484]	[0.3136]	[0.2506]	[0.3016]
$ln(\sigma^{X,MED})$	-7.01	-3.1224	-1.259	-2.8703	-6.5766	-9.2358
	[0.4286]	[0.3368]	[0.1717]	[0.408]	[0.4678]	[0.8323]

Note: This table presents the full set of parameter estimates for the benchmark model set up in Section 7.2 and detailed in Appendix D. Each column corresponds to the column with the same column number in Table B8, Panel B. Column 1 and 2 report the results of estimation that cover STEM students whose score is between 40% and 60% of the population. Column 3 and 4 report the results of estimation that cover STEM students whose score is between 60% and 80% of the population. Column 5 and 6 report the results of estimation that cover STEM students whose score is between 80% and 100% of the population. Odd columns report the results of the one-type rational model. Even columns report the results of the mixture model.

Table B10: Major Preference and its Impact on Risk Taking

	(1)	(2)	(3)	(4)	(5)	(6)
	Major Top Concern		Estimated Prob		Subjective Beliefs	
SES Index (Normalized)	-2.24%**	-2.66%**				
	(0.92%)	(1.17%)				
Major Top Concern			3.25%	4.09%	8.94%***	8.01%***
			(2.85%)	(3.00%)	(2.43%)	(2.51%)
Share of Major Top Concern	13.7%					
Implied Impact on 1st Choices			0.4%	0.6%	1.2%	1.1%
Priority Score	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Variables	No	Yes	No	Yes	No	Yes
College Preferences	No	Yes	No	Yes	No	Yes
Number of Observations	1412	1412	1386	1386	1412	1412
R squared	0.009	0.091	0.138	0.201	0.035	0.087

Note: Columns 1 and 2 present regressions that examine whether share of survey takers who think major is their top concern is correlated with SES Index. Columns 3 and 4 present the regression that examines whether those who declare major to be of top concern take different amount of risks on their first choices, in terms of the estimated unconditional admission probability. Columns 5 and 6 examine whether those who declare major to be of top concern take different amount of risks on their first choices, in terms of subjective probability. Columns 1,3,5 only control for priority score, whereas Columns 2,4,6 additionally control for demographics as well as stated college preferences. The share of people who think major is most important have been reported below the estimate for Columns 1 and 2. The implied impact of major consideration on the risk-taking of first choices is reported below the estimated coefficient in Columns 3,4,5,6. This is calculated as the product of the share of people who think major is the most important, and the average of additional cautiousness for the first choices among this group of people. This table is helpful for the discussion in Section E.4.

Table B11: Value of Moments: 40 - 60 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged) 1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	48.55%	49.56%	54.96%	45.56%
	(1.07%)	(1.32%)	(1.21%)	(1.31%)
Mean Assignment Probability of 2nd Choice	64.96%	70.22%	74.05%	67.54%
	(0.98%)	(1.18%)	(1.02%)	(1.18%)
Mean Assignment Probability of 3rd Choice	77.15%	81.92%	83.22%	79.63%
	(0.88%)	(0.99%)	(0.87%)	(1.02%)
Mean Assignment Probability of 4th Choice	87.73%	89.83%	92.26%	91.82%
	(0.7%)	(0.81%)	(0.64%)	(0.72%)
Share of Reversals R≥75%	13.85%	9.22%	7.53%	6.88%
	(0.91%)	(0.98%)	(0.83%)	(0.87%)
Share of Reversals R≥50%	20.63%	15.41%	13.5%	15.5%
	(1.07%)	(1.22%)	(1.08%)	(1.25%)
Share of Reversals R≥25%	31.73%	25.42%	23.97%	26.92%
	(1.23%)	(1.48%)	(1.35%)	(1.53%)
Share of Reversals R≥0%	60.8%	56.36%	54.89%	55.36%
	(1.29%)	(1.68%)	(1.57%)	(1.72%)
Competitiveness(Normalized) of Admitting College Mean	0.384	0.3678	0.3876	0.3632
	(0.0077)	(0.0099)	(0.0095)	(0.0105)
Share of Admission	96.02%	96.06%	97.55%	97.79%
	(0.52%)	(0.66%)	(0.49%)	(0.51%)
Competitiveness(Normalized) Mean: First Choices	-0.107	-0.1442	-0.2118	-0.0746
	(0.0142)	(0.0165)	(0.0149)	(0.0171)
Distance(Normalized) Mean: First Choices	-0.8255	-0.5104	-0.4462	-0.0974
	(0.0098)	(0.0118)	(0.0111)	(0.014)
STEM Concentration Share: First Choices	39.82%	44.21%	44.03%	48.37%
	(0.8%)	(1.09%)	(1.09%)	(1.14%)
Finance Concentration Share: First Choices	7.4%	8.66%	7.05%	6.99%
	(0.4%)	(0.74%)	(0.75%)	(1.06%)
Medical School Share: First Choices	18.3%	14.17%	14.09%	10.96%
	(0.7%)	(1.12%)	(1.06%)	(1.23%)
Competitiveness(Normalized) Mean: Second Choices	-0.2998	-0.3635	-0.4059	-0.3054
	(0.0126)	(0.0151)	(0.013)	(0.0143)
Distance(Normalized) Mean: Second Choices	-0.6479	-0.5372	-0.4028	-0.0053
	(0.0084)	(0.01)	(0.01)	(0.0129)
STEM Concentration Share: Second Choices	45.01%	45.14%	49.16%	50.23%
	(0.85%)	(1.07%)	(1.11%)	(1.15%)
Finance Concentration Share: Second Choices	8.1%	10.52%	6.52%	9.04%
	(0.52%)	(0.78%)	(0.64%)	(1.03%)
Medical School Share: Second Choices	11.84%	10.86%	11.85%	7.75%
	(0.83%)	(1.12%)	(1.15%)	(1.29%)
Competitiveness(Normalized) Mean: Third Choices	-0.456	-0.5116	-0.5213	-0.4475
	(0.0123)	(0.0133)	(0.0122)	(0.0134)
Distance(Normalized) Mean: Third Choices	-0.7354	-0.538	-0.3114	-0.0846
	(0.0082)	(0.0096)	(0.0086)	(0.0116)
STEM Concentration Share: Third Choices	45.34%	48.08%	47.67%	51.43%
	(0.82%)	(1.18%)	(1.13%)	(1.17%)
Finance Concentration Share: Third Choices	8.39%	8.15%	7.09%	8.71%
	(0.42%)	(0.7%)	(0.65%)	(0.97%)
Medical School Share: Third Choices	10.95%	8.96%	8.5%	6.32%
	(0.81%)	(1.14%)	(1.2%)	(1.33%)
Competitiveness(Normalized) Mean: Fourth Choices	-0.6332	-0.6766	-0.706	-0.6726
	(0.0113)	(0.0129)	(0.0108)	(0.0122)
Distance(Normalized) Mean: Fourth Choices	-1.0074	-0.7478	-0.5377	-0.3027
	(0.0068)	(0.008)	(0.0081)	(0.0104)
STEM Concentration Share: Fourth Choices	38.89%	39.76%	42.89%	45.34%
	(0.83%)	(1.05%)	(1.03%)	(1.1%)
Finance Concentration Share: Fourth Choices	4.43%	5.51%	5.52%	4.35%
	(0.43%)	(0.57%)	(0.6%)	(0.85%)
Medical School Share: Fourth Choices	12.16%	9.34%	7.43%	8.1%
	(0.73%)	(1.05%)	(1.06%)	(1.24%)

Note: This table presents the point estimate and standard error of moments for structural estimation in Section 7.3. The moments are calculated using the science-track student whose score is between 40th and 60th percentile among elite college eligible applicants. Standard errors are in the parenthesis.

Table B12: Fit of Benchmark Rational Model: 40 - 60 Percentile Test Score

	SES Quarter (1st = Most Disadvantaged)			
Varname	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	28.16%	29.66%	30.16%	30.24%
	[-20.39%]	[-19.9%]	[-24.8%]	[-15.32%]
Mean Assignment Probability of 2nd Choice	49.36%	50.26%	51.26%	51.6%
	[-15.6%]	[-19.96%]	[-22.79%]	[-15.94%]
Mean Assignment Probability of 3rd Choice	76.11%	76.58%	77.12%	77.36%
	[-1.05%]	[-5.34%]	[-6.1%]	[-2.27%]
Mean Assignment Probability of 4th Choice	99.84%	99.83%	99.81%	99.79%
	[12.11%]	[10%]	[7.56%]	[7.98%]
Share of Reversals R≥75%	8.21%	7.56%	7.6%	8.3%
	[-5.63%]	[-1.66%]	[0.07%]	[1.42%]
Share of Reversals R≥¿=50%	11.06%	10.29%	10.22%	10.32%
	[-9.57%]	[-5.12%]	[-3.28%]	[-5.18%]
Share of Reversals R≥25%	14.93%	13.58%	13.06%	12.51%
	[-16.8%]	[-11.84%]	[-10.91%]	[-14.41%]
Share of Reversals R≥0%	35.61%	33.77%	32.31%	30.3%
	[-25.19%]	[-22.59%]	[-22.58%]	[-25.07%]
Competitiveness(Normalized) of Admitting College Mean	0.3745	0.3627	0.3653	0.3823
	[-0.0095]	[-0.0051]	[-0.0223]	[0.0191]
Share of Admission	99.99%	100%	99.99%	99.98%
	[3.97%]	[3.93%]	[2.43%]	[2.2%]
Competitiveness(Normalized) Mean: First Choices	0.1638	0.1218	0.1208	0.1579
	[0.2708]	[0.266]	[0.3325]	[0.2325]
Distance(Normalized) Mean: First Choices	-0.751	-0.5381	-0.3889	-0.1086
	[0.0746]	[-0.0276]	[0.0573]	[-0.0112]
STEM Concentration Share: First Choices	39.36%	44.01%	46.95%	51.68%
	[-0.46%]	[-0.2%]	[2.92%]	[3.31%]
Finance Concentration Share: First Choices	9.02%	9.6%	9.09%	8.12%
	[1.61%]	[0.94%]	[2.04%]	[1.13%]
Medical School Share: First Choices	15.68%	12.98%	11.6%	8.48%
	[-2.62%]	[-1.19%]	[-2.49%]	[-2.48%]
Competitiveness(Normalized) Mean: Second Choices	-0.1284	-0.1533	-0.1595	-0.1408
	[0.1714]	[0.2102]	[0.2464]	[0.1646]
Distance(Normalized) Mean: Second Choices	-0.7573	-0.5321	-0.3734	-0.0683
	[-0.1093]	[0.0051]	[0.0294]	[-0.063]
STEM Concentration Share: Second Choices	44.05%	47.84%	48.98%	50.72%
	[-0.96%]	[2.7%]	[-0.18%]	[0.49%]
Finance Concentration Share: Second Choices	8.71%	9.53%	9.4%	8.54%
	[0.61%]	[-0.99%]	[2.88%]	[-0.5%]
Medical School Share: Second Choices	16.72%	14.96%	15.4%	15.75%
	[4.87%]	[4.1%]	[3.56%]	[8%]
Competitiveness(Normalized) Mean: Third Choices	-0.3934	-0.4096	-0.4111	-0.3976
	[0.0625]	[0.102]	[0.1102]	[0.0499]
Distance(Normalized) Mean: Third Choices	-0.8113	-0.5897	-0.4365	-0.1336
	[-0.0759]	[-0.0517]	[-0.1251]	[-0.049]
STEM Concentration Share: Third Choices	42.05%	44.27%	44.17%	44.18%
	[-3.29%]	[-3.81%]	[-3.5%]	[-7.25%]
Finance Concentration Share: Third Choices	11.03%	11.98%	12.5%	12.16%
	[2.64%]	[3.83%]	[5.42%]	[3.44%]
Medical School Share: Third Choices	15.87%	13.33%	12.46%	12.92%
	[4.92%]	[4.37%]	[3.96%]	[6.6%]
Competitiveness(Normalized) Mean: Fourth Choices	-0.8345	-0.8378	-0.8329	-0.818
	[-0.2012]	[-0.1612]	[-0.127]	[-0.1454]
Distance(Normalized) Mean: Fourth Choices	-0.903	-0.6735	-0.5153	-0.2077
	[0.1044]	[0.0743]	[0.0224]	[0.0949]
STEM Concentration Share: Fourth Choices	45.1%	47.26%	47.05%	44.11%
	[6.22%]	[7.49%]	[4.16%]	[-1.23%]
Finance Concentration Share: Fourth Choices	5.17%	5.96%	6.92%	8.68%
	[0.75%]	[0.45%]	[1.4%]	[4.33%]
Medical School Share: Fourth Choices	19.99%	17.03%	15.63%	13.37%
	[7.83%]	[7.69%]	[8.2%]	[5.27%]

Note: This table presents details of the fit of rational benchmark model in Section 7.4 and Table 4. The predicted value are calculated using the science-track student whose score is between 40th and 60th percentile among elite college eligible applicants. Prediction error, as defined by predicted value minus the value of moments, are in squared brackets.

Table B13: Fit of Benchmark Mixture Model: 40 - 60 Percentile Test Score

	SES Quarter (1st = Most Disadvantaged)			
Varname	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	59.22%	58.88%	58.23%	57.7%
	[10.67%]	[9.32%]	[3.27%]	[12.14%]
Mean Assignment Probability of 2nd Choice	64.84%	65.26%	64.77%	64.91%
	[-0.12%]	[-4.96%]	[-9.29%]	[-2.63%]
Mean Assignment Probability of 3rd Choice	76.62%	77.65%	78.2%	78.75%
	[-0.54%]	[-4.27%]	[-5.01%]	[-0.88%]
Mean Assignment Probability of 4th Choice	92.12%	94.11%	95.25%	96.82%
	[4.39%]	[4.28%]	[2.99%]	[5.01%]
Share of Reversals R≥75%	4.16%	3.52%	3.14%	3.42%
	[-9.68%]	[-5.7%]	[-4.39%]	[-3.46%]
Share of Reversals R≥50%	6.98%	6.5%	6.23%	6.75%
	[-13.65%]	[-8.91%]	[-7.28%]	[-8.76%]
Share of Reversals R≥25%	14.36%	14.07%	13.93%	14.09%
	[-17.38%]	[-11.35%]	[-10.05%]	[-12.83%]
Share of Reversals R≥0%	56.59%	53.26%	50.54%	46.26%
	[-4.2%]	[-3.1%]	[-4.35%]	[-9.1%]
Competitiveness(Normalized) of Admitting College Mean	0.4563	0.4621	0.471	0.4924
	[0.0723]	[0.0943]	[0.0834]	[0.1291]
Share of Admission	99.54%	99.7%	99.78%	99.85%
	[3.51%]	[3.64%]	[2.23%]	[2.06%]
Competitiveness(Normalized) Mean: First Choices	-0.2064	-0.2391	-0.2384	-0.2287
	[-0.0994]	[-0.0949]	[-0.0266]	[-0.1541]
Distance(Normalized) Mean: First Choices	-0.8163	-0.5128	-0.3604	-0.1043
	[0.0092]	[-0.0024]	[0.0858]	[-0.0069]
STEM Concentration Share: First Choices	38.12%	40.58%	41.35%	42.86%
	[-1.7%]	[-3.63%]	[-2.68%]	[-5.51%]
Finance Concentration Share: First Choices	7.58%	8.92%	8.98%	9.85%
	[0.17%]	[0.25%]	[1.93%]	[2.86%]
Medical School Share: First Choices	13.76%	12.37%	12.14%	13.23%
	[-4.54%]	[-1.8%]	[-1.95%]	[2.28%]
Competitiveness(Normalized) Mean: Second Choices	-0.3004	-0.3364	-0.3341	-0.3269
	[-0.0006]	[0.0271]	[0.0718]	[-0.0216]
Distance(Normalized) Mean: Second Choices	-0.7857	-0.514	-0.3583	-0.1075
	[-0.1377]	[0.0233]	[0.0445]	[-0.1023]
STEM Concentration Share: Second Choices	41.22%	43.18%	44.25%	45.39%
	[-3.79%]	[-1.95%]	[-4.91%]	[-4.84%]
Finance Concentration Share: Second Choices	7.22%	8.37%	8.68%	8.97%
	[-0.88%]	[-2.15%]	[2.16%]	[-0.06%]
Medical School Share: Second Choices	12.99%	11.01%	10.37%	10.24%
	[1.15%]	[0.15%]	[-1.47%]	[2.49%]
Competitiveness(Normalized) Mean: Third Choices	-0.4423	-0.4754	-0.4815	-0.4771
	[0.0137]	[0.0362]	[0.0398]	[-0.0296]
Distance(Normalized) Mean: Third Choices	-0.8386	-0.5564	-0.3989	-0.132
	[-0.1032]	[-0.0183]	[-0.0875]	[-0.0475]
STEM Concentration Share: Third Choices	43.24%	45.05%	46.5%	48.19%
	[-2.11%]	[-3.03%]	[-1.18%]	[-3.25%]
Finance Concentration Share: Third Choices	8.39%	10.11%	10.46%	11.31%
	[0%]	[1.96%]	[3.38%]	[2.6%]
Medical School Share: Third Choices	13.91%	10.72%	8.68%	6.52%
	[2.97%]	[1.76%]	[0.18%]	[0.2%]
Competitiveness(Normalized) Mean: Fourth Choices	-0.7101	-0.7497	-0.7682	-0.7934
	[-0.0768]	[-0.073]	[-0.0622]	[-0.1208]
Distance(Normalized) Mean: Fourth Choices	-0.9644	-0.69	-0.5176	-0.2172
	[0.043]	[0.0578]	[0.0201]	[0.0854]
STEM Concentration Share: Fourth Choices	43.27%	47.21%	49.41%	53.14%
	[4.38%]	[7.45%]	[6.52%]	[7.8%]
Finance Concentration Share: Fourth Choices	6.15%	6.63%	6.95%	7.93%
	[1.72%]	[1.12%]	[1.43%]	[3.57%]
Medical School Share: Fourth Choices	15.54%	12.81%	11.06%	7.38%
	[3.38%]	[3.47%]	[3.63%]	[-0.72%]

Note: This table presents details of the fit of mixture model in Section 7.4 and Table 4. The predicted value are calculated using the science-track student whose score is between 40th and 60th percentile among elite college eligible applicants. Prediction error, as defined by predicted value minus the value of moments, are in squared brackets.

Table B14: Value of Moments: 60 - 80 Percentile Test Score

	SES Quarter (1st = Most Disadvantaged)			
Varname	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	54.14%	53.11%	52.96%	45.48%
	(1.02%)	(1.24%)	(1.11%)	(1.01%)
Mean Assignment Probability of 2nd Choice	70.12%	73.36%	72.27%	69.73%
	(0.9%)	(1.01%)	(0.94%)	(0.86%)
Mean Assignment Probability of 3rd Choice	80.5%	84.08%	85.36%	82.37%
	(0.79%)	(0.83%)	(0.73%)	(0.68%)
Mean Assignment Probability of 4th Choice	90.51%	92.74%	93.13%	93.17%
	(0.6%)	(0.6%)	(0.55%)	(0.48%)
Share of Reversals R≥75%	5.99%	2.93%	3.15%	2.63%
	(0.67%)	(0.6%)	(0.56%)	(0.49%)
Share of Reversals R≥50%	14.5%	8.91%	7.93%	7.34%
	(1%)	(1.01%)	(0.87%)	(0.79%)
Share of Reversals R≥25%	27.27%	18.93%	18.31%	17.48%
	(1.26%)	(1.38%)	(1.25%)	(1.15%)
Share of Reversals R≥0%	54.69%	51.53%	49.03%	51.45%
	(1.41%)	(1.76%)	(1.61%)	(1.52%)
Competitiveness(Normalized) of Admitting College Mean	0.4634	0.3866	0.3675	0.3469
	(0.0119)	(0.0132)	(0.0121)	(0.0116)
Share of Admission	97.56%	97.92%	97.97%	98.64%
	(0.44%)	(0.5%)	(0.46%)	(0.35%)
Competitiveness(Normalized) Mean: First Choices	0.3794	0.4188	0.4187	0.5455
	(0.0159)	(0.018)	(0.0167)	(0.0147)
Distance(Normalized) Mean: First Choices	-0.578	-0.3198	-0.178	0.0791
	(0.0123)	(0.0146)	(0.014)	(0.0141)
STEM Concentration Share: First Choices	40.5%	42.12%	44.35%	45.2%
	(0.76%)	(1.02%)	(0.88%)	(0.91%)
Finance Concentration Share: First Choices	7.64%	11.11%	7.63%	6.79%
	(0.42%)	(0.57%)	(0.61%)	(0.59%)
Medical School Share: First Choices	16.47%	12.7%	10.68%	7.34%
	(0.93%)	(1.31%)	(1.14%)	(1.19%)
Competitiveness(Normalized) Mean: Second Choices	0.1929	0.1811	0.2058	0.2998
	(0.0149)	(0.016)	(0.0152)	(0.013)
Distance(Normalized) Mean: Second Choices	-0.5204	-0.2852	-0.2205	0.052
	(0.0115)	(0.015)	(0.0132)	(0.0137)
STEM Concentration Share: Second Choices	42.22%	45.58%	46.06%	49%
	(0.79%)	(1.11%)	(0.97%)	(0.88%)
Finance Concentration Share: Second Choices	8.94%	11.92%	9.31%	7.74%
	(0.45%)	(0.65%)	(0.64%)	(0.7%)
Medical School Share: Second Choices	13.81%	9.58%	10.95%	6.74%
	(0.9%)	(1.28%)	(1.19%)	(1.17%)
Competitiveness(Normalized) Mean: Third Choices	0.022	0.0086	0.0164	0.1283
	(0.0144)	(0.017)	(0.0153)	(0.0135)
Distance(Normalized) Mean: Third Choices	-0.4913	-0.3728	-0.1769	0.0495
	(0.0112)	(0.0141)	(0.0125)	(0.0131)
STEM Concentration Share: Third Choices	44.54%	46.96%	46.45%	51.93%
	(0.8%)	(1.02%)	(0.92%)	(0.92%)
Finance Concentration Share: Third Choices	9.54%	11.55%	8.87%	10.73%
	(0.51%)	(0.79%)	(0.75%)	(0.75%)
Medical School Share: Third Choices	11.4%	9.44%	9.71%	6.61%
	(0.92%)	(1.23%)	(1.23%)	(1.22%)
Competitiveness(Normalized) Mean: Fourth Choices	-0.2358	-0.2258	-0.2299	-0.1447
	(0.0147)	(0.0173)	(0.0161)	(0.0144)
Distance(Normalized) Mean: Fourth Choices	-0.8549	-0.5139	-0.3418	-0.0737
	(0.0099)	(0.0123)	(0.0115)	(0.0121)
STEM Concentration Share: Fourth Choices	39.24%	44.33%	48.15%	48.79%
	(0.76%)	(1.06%)	(0.95%)	(0.95%)
Finance Concentration Share: Fourth Choices	8.69%	9.3%	6.76%	9.67%
	(0.42%)	(0.75%)	(0.73%)	(0.79%)
Medical School Share: Fourth Choices	12.24%	11.72%	11.09%	6.78%
	(0.87%)	(1.21%)	(1.12%)	(1.13%)

Note: This table presents the point estimate and standard error of moments for structural estimation in Section 7.3. The moments are calculated using the science-track student whose score is between 60th and 80th percentile among elite college eligible applicants. Standard errors are in the parenthesis.

Table B15: Fit of Benchmark Rational Model: 60 - 80 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged) 1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	33.86%	32.29%	31.51%	30.82%
	[-20.27%]	[-20.82%]	[-21.44%]	[-14.65%]
Mean Assignment Probability of 2nd Choice	53.08%	51.81%	51.21%	50.3%
	[-17.04%]	[-21.55%]	[-21.05%]	[-19.43%]
Mean Assignment Probability of 3rd Choice	77.57%	77.56%	77.43%	76.87%
	[-2.93%]	[-6.52%]	[-7.92%]	[-5.5%]
Mean Assignment Probability of 4th Choice	99.43%	99.32%	99.22%	98.96%
	[8.93%]	[6.58%]	[6.09%]	[5.79%]
Share of Reversals R≥75%	3.43%	2.89%	2.63%	2.02%
	[-2.56%]	[-0.04%]	[-0.52%]	[-0.61%]
Share of Reversals R≥50%	7.9%	6.55%	6.1%	4.97%
	[-6.6%]	[-2.36%]	[-1.84%]	[-2.37%]
Share of Reversals ≥25%	15.22%	12.92%	11.79%	9.84%
	[-12.04%]	[-6.01%]	[-6.52%]	[-7.64%]
Share of Reversals R≥0%	39.62%	37.59%	36.3%	33.13%
	[-15.06%]	[-13.93%]	[-12.74%]	[-18.32%]
Competitiveness(Normalized) of Admitting College Mean	0.3689	0.3489	0.3453	0.3321
	[-0.0944]	[-0.0377]	[-0.0222]	[-0.0148]
Share of Admission	99.94%	99.93%	99.93%	99.86%
	[2.38%]	[2.01%]	[1.97%]	[1.22%]
Competitiveness(Normalized) Mean: First Choices	0.6925	0.6886	0.6996	0.7433
	[0.3131]	[0.2697]	[0.2809]	[0.1978]
Distance(Normalized) Mean: First Choices	-0.6088	-0.3851	-0.2444	0.016
	[-0.0308]	[-0.0653]	[-0.0665]	[-0.0632]
STEM Concentration Share: First Choices	41.48%	44.48%	46.24%	49.4%
	[0.97%]	[2.36%]	[1.88%]	[4.2%]
Finance Concentration Share: First Choices	9.55%	10.06%	9.45%	8.69%
	[1.91%]	[-1.05%]	[1.83%]	[1.9%]
Medical School Share: First Choices	19.36%	15.43%	13.03%	8.62%
	[2.89%]	[2.73%]	[2.35%]	[1.28%]
Competitiveness(Normalized) Mean: Second Choices	0.4923	0.4969	0.5088	0.5603
	[0.2994]	[0.3158]	[0.303]	[0.2606]
Distance(Normalized) Mean: Second Choices	-0.6017	-0.3798	-0.2404	0.0267
	[-0.0812]	[-0.0946]	[-0.0199]	[-0.0254]
STEM Concentration Share: Second Choices	42.22%	44.99%	47.03%	50.21%
	[0.01%]	[-0.59%]	[0.97%]	[1.21%]
Finance Concentration Share: Second Choices	8.39%	9.28%	9.01%	8.91%
	[-0.55%]	[-2.64%]	[-0.31%]	[1.17%]
Medical School Share: Second Choices	17.06%	14.2%	11.74%	8.25%
	[3.25%]	[4.61%]	[0.78%]	[1.51%]
Competitiveness(Normalized) Mean: Third Choices	0.2384	0.2446	0.2577	0.3073
	[0.2164]	[0.236]	[0.2413]	[0.179]
Distance(Normalized) Mean: Third Choices	-0.622	-0.3906	-0.2425	0.0356
	[-0.1307]	[-0.0178]	[-0.0656]	[-0.0139]
STEM Concentration Share: Third Choices	43.22%	45.85%	47.49%	50.58%
	[-1.32%]	[-1.11%]	[1.04%]	[-1.35%]
Finance Concentration Share: Third Choices	6.52%	6.93%	7.2%	7.18%
	[-3.02%]	[-4.62%]	[-1.67%]	[-3.55%]
Medical School Share: Third Choices	12.72%	10.88%	9.28%	7.19%
	[1.32%]	[1.44%]	[-0.43%]	[0.59%]
Competitiveness(Normalized) Mean: Fourth Choices	-0.2976	-0.2602	-0.2363	-0.1777
	[-0.0617]	[-0.0344]	[-0.0064]	[-0.033]
Distance(Normalized) Mean: Fourth Choices	-0.6254	-0.3759	-0.2276	0.0548
	[0.2295]	[0.138]	[0.1142]	[0.1285]
STEM Concentration Share: Fourth Choices	44.24%	46.51%	48.07%	51.19%
	[5%]	[2.18%]	[-0.08%]	[2.4%]
Finance Concentration Share: Fourth Choices	9.95%	8.29%	6.99%	4.9%
	[1.26%]	[-1.01%]	[0.23%]	[-4.76%]
Medical School Share: Fourth Choices	9.46%	7.57%	6.77%	5.91%
	[-2.77%]	[-4.15%]	[-4.32%]	[-0.88%]

Note: This table presents details of the fit of rational benchmark model in Section 7.4 and Table 4. The predicted value are calculated using the science-track student whose score is between 60th and 80th percentile among elite college eligible applicants. Prediction error, as defined by predicted value minus the value of moments, are in squared brackets.

Table B16: Fit of Benchmark Mixture Model: 60 - 80 Percentile Test Score

	SES Quarter (1st = Most Disadvantaged)			
Varname	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	57.55%	55.46%	54.14%	52.76%
	[3.41%]	[2.35%]	[1.18%]	[7.29%]
Mean Assignment Probability of 2nd Choice	64.13%	63.22%	62.95%	62.94%
	[-5.99%]	[-10.14%]	[-9.32%]	[-6.79%]
Mean Assignment Probability of 3rd Choice	75.94%	77.11%	77.84%	79.25%
	[-4.55%]	[-6.97%]	[-7.52%]	[-3.12%]
Mean Assignment Probability of 4th Choice	90.24%	91.77%	92.92%	94.48%
	[-0.27%]	[-0.98%]	[-0.21%]	[1.32%]
Share of Reversals R≥75%	4.13%	2.46%	1.75%	0.81%
	[-1.86%]	[-0.47%]	[-1.41%]	[-1.82%]
Share of Reversals R≥50%	11.9%	8.65%	6.75%	4.27%
	[-2.6%]	[-0.26%]	[-1.19%]	[-3.06%]
Share of Reversals R≥25%	28.79%	24.93%	22.07%	17.78%
	[1.52%]	[6.01%]	[3.76%]	[0.3%]
Share of Reversals R≥0%	65.25%	62.69%	60.47%	58.04%
	[10.56%]	[11.16%]	[11.43%]	[6.59%]
Competitiveness(Normalized) of Admitting College Mean	0.5212	0.474	0.454	0.4304
	[0.0579]	[0.0874]	[0.0865]	[0.0835]
Share of Admission	99.03%	99.32%	99.57%	99.79%
	[1.47%]	[1.39%]	[1.61%]	[1.14%]
Competitiveness(Normalized) Mean: First Choices	0.3209	0.3608	0.388	0.4382
	[-0.0584]	[-0.0581]	[-0.0308]	[-0.1074]
Distance(Normalized) Mean: First Choices	-0.5789	-0.3384	-0.1999	0.0746
	[-0.0008]	[-0.0185]	[-0.022]	[-0.0045]
STEM Concentration Share: First Choices	39.73%	42.56%	45.27%	48.34%
	[-0.77%]	[0.44%]	[0.91%]	[3.14%]
Finance Concentration Share: First Choices	8.86%	8.97%	9.11%	8.69%
	[1.22%]	[-2.14%]	[1.48%]	[1.9%]
Medical School Share: First Choices	16.4%	12.08%	9.81%	7.21%
	[-0.07%]	[-0.62%]	[-0.87%]	[-0.13%]
Competitiveness(Normalized) Mean: Second Choices	0.257	0.2845	0.2999	0.3443
	[0.0641]	[0.1035]	[0.0942]	[0.0446]
Distance(Normalized) Mean: Second Choices	-0.5437	-0.3093	-0.1793	0.0901
	[-0.0233]	[-0.0241]	[0.0412]	[0.038]
STEM Concentration Share: Second Choices	38.81%	42.21%	44.21%	47.68%
	[-3.41%]	[-3.37%]	[-1.85%]	[-1.32%]
Finance Concentration Share: Second Choices	9.24%	9.56%	9.38%	9.53%
	[0.3%]	[-2.35%]	[0.06%]	[1.79%]
Medical School Share: Second Choices	15.35%	12.52%	10.58%	8.7%
	[1.54%]	[2.94%]	[-0.37%]	[1.96%]
Competitiveness(Normalized) Mean: Third Choices	0.1502	0.1625	0.1729	0.2075
	[0.1282]	[0.1539]	[0.1566]	[0.0792]
Distance(Normalized) Mean: Third Choices	-0.5674	-0.3575	-0.228	0.0434
	[-0.0761]	[0.0153]	[-0.051]	[-0.0061]
STEM Concentration Share: Third Choices	40.46%	43.58%	45.73%	48.68%
	[-4.09%]	[-3.37%]	[-0.72%]	[-3.24%]
Finance Concentration Share: Third Choices	7.98%	8.21%	8.29%	8.43%
	[-1.55%]	[-3.34%]	[-0.58%]	[-2.3%]
Medical School Share: Third Choices	13.64%	10.61%	9.48%	7.97%
	[2.25%]	[1.17%]	[-0.23%]	[1.37%]
Competitiveness(Normalized) Mean: Fourth Choices	-0.1944	-0.1838	-0.1745	-0.1264
	[0.0414]	[0.042]	[0.0554]	[0.0183]
Distance(Normalized) Mean: Fourth Choices	-0.7603	-0.5091	-0.3544	-0.0482
	[0.0946]	[0.0048]	[-0.0126]	[0.0255]
STEM Concentration Share: Fourth Choices	41.83%	45.46%	47.97%	51.02%
	[2.59%]	[1.13%]	[-0.19%]	[2.23%]
Finance Concentration Share: Fourth Choices	8.8%	8.94%	8.45%	7.54%
	[0.11%]	[-0.36%]	[1.69%]	[-2.13%]
Medical School Share: Fourth Choices	15.5%	11.69%	9.65%	7.35%
	[3.27%]	[-0.03%]	[-1.44%]	[0.57%]

Note: This table presents details of the fit of mixture model in Section 7.4 and Table 4. The predicted value are calculated using the science-track student whose score is between 60th and 80th percentile among elite college eligible applicants. Prediction error, as defined by predicted value minus the value of moments, are in squared brackets.

Table B17: Value of Moments: 80 - 100 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged) 1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	62.33%	61.76%	62.19%	55.77%
	(1.23%)	(1.38%)	(1.15%)	(0.82%)
Mean Assignment Probability of 2nd Choice	81.55%	82.78%	83.32%	78.51%
	(0.88%)	(0.91%)	(0.76%)	(0.58%)
Mean Assignment Probability of 3rd Choice	90.19%	90.63%	91.4%	89.97%
	(0.65%)	(0.71%)	(0.53%)	(0.39%)
Mean Assignment Probability of 4th Choice	95.1%	96.38%	96.99%	96.59%
	(0.51%)	(0.44%)	(0.31%)	(0.24%)
Share of Reversals R≥75%	2.82%	2.13%	1.47%	1.69%
	(0.58%)	(0.57%)	(0.41%)	(0.3%)
Share of Reversals R≥50%	6.98%	4.56%	3.06%	3.83%
	(0.9%)	(0.82%)	(0.59%)	(0.45%)
Share of Reversals R≥25%	16.28%	10.03%	10.32%	10.33%
	(1.31%)	(1.18%)	(1.04%)	(0.72%)
Share of Reversals R≥0%	49.33%	44.38%	43.99%	40.57%
	(1.77%)	(1.96%)	(1.69%)	(1.16%)
Competitiveness(Normalized) of Admitting College Mean	0.423	0.3781	0.3492	0.307
	(0.0185)	(0.0168)	(0.0135)	(0.0094)
Share of Admission	98.41%	98.78%	99.32%	99.73%
	(0.44%)	(0.43%)	(0.28%)	(0.12%)
Competitiveness(Normalized) Mean: First Choices	1.3059	1.3551	1.4226	1.6837
	(0.0228)	(0.0266)	(0.024)	(0.0167)
Distance(Normalized) Mean: First Choices	-0.341	-0.3134	-0.1472	0.0324
	(0.0163)	(0.018)	(0.0158)	(0.0116)
STEM Concentration Share: First Choices	38.8%	38.91%	34.81%	32.97%
	(1.18%)	(1.22%)	(0.96%)	(0.57%)
Finance Concentration Share: First Choices	9.18%	9.73%	9.86%	9.57%
	(0.55%)	(0.72%)	(0.76%)	(0.58%)
Medical School Share: First Choices	10.04%	9.57%	7.14%	4.7%
	(1.08%)	(1.24%)	(1.17%)	(0.85%)
Competitiveness(Normalized) Mean: Second Choices	1.0676	1.1332	1.1852	1.4278
	(0.0207)	(0.0229)	(0.0227)	(0.015)
Distance(Normalized) Mean: Second Choices	-0.3268	-0.1971	-0.0907	0.043
	(0.0158)	(0.0181)	(0.0154)	(0.0112)
STEM Concentration Share: Second Choices	42.18%	39.45%	42.3%	35.26%
	(1.15%)	(1.07%)	(1.03%)	(0.62%)
Finance Concentration Share: Second Choices	8.93%	11.86%	8.97%	8.23%
	(0.6%)	(0.65%)	(0.75%)	(0.58%)
Medical School Share: Second Choices	9.18%	8.63%	5.63%	3.52%
	(1.13%)	(1.39%)	(1.19%)	(0.87%)
Competitiveness(Normalized) Mean: Third Choices	0.9189	0.9631	1.0387	1.2415
	(0.0212)	(0.0243)	(0.0224)	(0.0148)
Distance(Normalized) Mean: Third Choices	-0.3	-0.199	-0.0996	0.033
	(0.016)	(0.0176)	(0.0155)	(0.011)
STEM Concentration Share: Third Choices	41.88%	47.13%	42.28%	37.49%
	(1.17%)	(1.18%)	(1.03%)	(0.71%)
Finance Concentration Share: Third Choices	9%	9.77%	8.99%	9.04%
	(0.65%)	(0.77%)	(0.72%)	(0.57%)
Medical School Share: Third Choices	9.38%	6.67%	5.76%	3.92%
	(1.08%)	(1.36%)	(1.22%)	(0.91%)
Competitiveness(Normalized) Mean: Fourth Choices	0.6635	0.6843	0.7838	0.981
	(0.0234)	(0.0265)	(0.0241)	(0.0161)
Distance(Normalized) Mean: Fourth Choices	-0.4375	-0.3218	-0.1766	0.012
	(0.0156)	(0.0172)	(0.0148)	(0.0109)
STEM Concentration Share: Fourth Choices	41.21%	42.41%	40.52%	38.38%
	(1.1%)	(1.26%)	(0.91%)	(0.67%)
Finance Concentration Share: Fourth Choices	8.47%	10.92%	10.37%	7.34%
	(0.64%)	(0.67%)	(0.79%)	(0.56%)
Medical School Share: Fourth Choices	11.17%	9.34%	7.42%	5.78%
	(1.14%)	(1.36%)	(1.22%)	(0.92%)

Note: This table presents the point estimate and standard error of moments for structural estimation in Section 7.3. The moments are calculated using the science-track student whose score is between 80th and 100th percentile among elite college eligible applicants. Standard errors are in the parenthesis.

Table B18: Fit of Benchmark Rational Model: 80 - 100 Percentile Test Score

	SES Quarter (1st = Most Disadvantaged)			
Varname	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	39.19%	37.61%	37.3%	38.23%
	[-23.13%]	[-24.14%]	[-24.89%]	[-17.55%]
Mean Assignment Probability of 2nd Choice	68.8%	67.83%	66.63%	64.14%
	[-12.75%]	[-14.96%]	[-16.69%]	[-14.37%]
Mean Assignment Probability of 3rd Choice	89.53%	89.31%	88.44%	87.2%
	[-0.66%]	[-1.32%]	[-2.97%]	[-2.77%]
Mean Assignment Probability of 4th Choice	99.42%	99.61%	99.26%	99.31%
	[4.32%]	[3.24%]	[2.27%]	[2.73%]
Share of Reversals R≥75%	4.76%	3.52%	3.41%	3.32%
	[1.94%]	[1.4%]	[1.94%]	[1.62%]
Share of Reversals R≥50%	7.67%	5.75%	5.83%	6.28%
	[0.69%]	[1.19%]	[2.77%]	[2.45%]
Share of Reversals R≥25%	15.07%	12.56%	13.29%	13.28%
	[-1.21%]	[2.53%]	[2.98%]	[2.94%]
Share of Reversals R≥0%	38.59%	36.47%	35.96%	33.42%
	[-10.74%]	[-7.9%]	[-8.03%]	[-7.15%]
Competitiveness(Normalized) of Admitting College Mean	0.4013	0.3614	0.3465	0.3408
	[-0.0217]	[-0.0167]	[-0.0028]	[0.0338]
Share of Admission	100%	100%	100%	100%
	[1.59%]	[1.22%]	[0.68%]	[0.27%]
Competitiveness(Normalized) Mean: First Choices	1.5675	1.6217	1.6821	1.8379
	[0.2616]	[0.2666]	[0.2595]	[0.1541]
Distance(Normalized) Mean: First Choices	-0.3238	-0.2502	-0.1837	0.1079
	[0.0173]	[0.0632]	[-0.0365]	[0.0755]
STEM Concentration Share: First Choices	42.07%	40.22%	39.33%	36.77%
	[3.27%]	[1.32%]	[4.53%]	[3.8%]
Finance Concentration Share: First Choices	8.71%	9.42%	9.48%	9.71%
	[-0.47%]	[-0.31%]	[-0.39%]	[0.14%]
Medical School Share: First Choices	10.41%	8.11%	6.78%	4.09%
	[0.38%]	[-1.46%]	[-0.36%]	[-0.61%]
Competitiveness(Normalized) Mean: Second Choices	1.2752	1.3493	1.4339	1.6405
	[0.2076]	[0.2161]	[0.2487]	[0.2126]
Distance(Normalized) Mean: Second Choices	-0.3153	-0.2546	-0.1991	0.08
	[0.0115]	[-0.0574]	[-0.1084]	[0.0369]
STEM Concentration Share: Second Choices	42.61%	40.44%	39.16%	35.97%
	[0.43%]	[1%]	[-3.14%]	[0.71%]
Finance Concentration Share: Second Choices	8.5%	9.28%	9.22%	8.84%
	[-0.44%]	[-2.58%]	[0.26%]	[0.61%]
Medical School Share: Second Choices	9.89%	7.62%	6.15%	3.76%
	[0.71%]	[-1.01%]	[0.52%]	[0.24%]
Competitiveness(Normalized) Mean: Third Choices	1.0099	1.0879	1.1847	1.4037
	[0.091]	[0.1248]	[0.146]	[0.1622]
Distance(Normalized) Mean: Third Choices	-0.3025	-0.2461	-0.1793	0.0792
	[-0.0025]	[-0.0471]	[-0.0797]	[0.0462]
STEM Concentration Share: Third Choices	43.4%	40.88%	39.49%	35.66%
	[1.52%]	[-6.26%]	[-2.79%]	[-1.83%]
Finance Concentration Share: Third Choices	8.58%	9.28%	9.18%	8.95%
	[-0.42%]	[-0.49%]	[0.2%]	[-0.09%]
Medical School Share: Third Choices	9.76%	7.48%	6.13%	3.88%
	[0.38%]	[0.82%]	[0.37%]	[-0.05%]
Competitiveness(Normalized) Mean: Fourth Choices	0.5552	0.6517	0.7469	0.9699
	[-0.1083]	[-0.0326]	[-0.0369]	[-0.0111]
Distance(Normalized) Mean: Fourth Choices	-0.2793	-0.2191	-0.1715	0.0402
	[0.1582]	[0.1027]	[0.0051]	[0.0282]
STEM Concentration Share: Fourth Choices	43.94%	41%	39.57%	35.97%
	[2.73%]	[-1.4%]	[-0.94%]	[-2.41%]
Finance Concentration Share: Fourth Choices	8.67%	9.35%	9.43%	9.61%
	[0.2%]	[-1.57%]	[-0.93%]	[2.27%]
Medical School Share: Fourth Choices	9.95%	8.09%	6.96%	4.57%
	[-1.21%]	[-1.24%]	[-0.46%]	[-1.21%]

Note: This table presents details of the fit of rational benchmark model in Section 7.4 and Table 4. The predicted value are calculated using the science-track student whose score is between 80th and 100th percentile among elite college eligible applicants. Prediction error, as defined by predicted value minus the value of moments, are in squared brackets.

Table B19: Fit of Mixture Model: 80 - 100 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged) 1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	70.94% [8.61%]	67.9% [6.14%]	66.06% [3.87%]	63.71% [7.94%]
Mean Assignment Probability of 2nd Choice	81.36% [-0.19%]	79.25% [-3.53%]	77.4% [-5.92%]	75.03% [-3.48%]
Mean Assignment Probability of 3rd Choice	89.09% [-1.1%]	87.94% [-2.69%]	87.42% [-3.98%]	86.78% [-3.19%]
Mean Assignment Probability of 4th Choice	97.29% [2.19%]	97.4% [1.02%]	97.38% [0.39%]	97.49% [0.9%]
Share of Reversals R≥75%	2.45% [-0.37%]	2.85% [0.72%]	2.94% [1.47%]	4.04% [2.35%]
Share of Reversals R≥50%	5.61% [-1.37%]	6.26% [1.71%]	6.45% [3.39%]	7.7% [3.87%]
Share of Reversals R≥25%	9.91% [-6.37%]	11.06% [1.03%]	11.81% [1.49%]	13.04% [2.7%]
Share of Reversals R≥0%	58.84% [9.52%]	57.06% [12.69%]	56.02% [12.03%]	53.96% [13.39%]
Competitiveness(Normalized) of Admitting College Mean	0.525 [0.102]	0.505 [0.1269]	0.4894 [0.1402]	0.4717 [0.1647]
Share of Admission	99.72% [1.31%]	99.72% [0.93%]	99.68% [0.37%]	99.69% [-0.04%]
Competitiveness(Normalized) Mean: First Choices	1.2309 [-0.0749]	1.2911 [-0.064]	1.3683 [-0.0544]	1.5698 [-0.1139]
Distance(Normalized) Mean: First Choices	-0.3479 [-0.0069]	-0.2025 [0.1109]	-0.1318 [0.0154]	0.0557 [0.0233]
STEM Concentration Share: First Choices	42.54% [3.74%]	41.04% [2.14%]	40.14% [5.34%]	37.48% [4.52%]
Finance Concentration Share: First Choices	9.27% [0.09%]	9.64% [-0.09%]	9.61% [-0.25%]	8.96% [-0.6%]
Medical School Share: First Choices	10.02% [-0.02%]	6.67% [-2.9%]	4.73% [-2.41%]	2.13% [-2.57%]
Competitiveness(Normalized) Mean: Second Choices	1.0832 [0.0156]	1.1446 [0.0114]	1.2309 [0.0457]	1.4415 [0.0136]
Distance(Normalized) Mean: Second Choices	-0.2974 [0.0293]	-0.1577 [0.0394]	-0.0871 [0.0036]	0.094 [0.051]
STEM Concentration Share: Second Choices	45.64% [3.46%]	44.3% [4.86%]	43.11% [0.81%]	38.2% [2.94%]
Finance Concentration Share: Second Choices	10.05% [1.12%]	10.49% [-1.38%]	10.14% [1.17%]	9.46% [1.23%]
Medical School Share: Second Choices	9.66% [0.48%]	6.81% [-1.82%]	5.19% [-0.44%]	2.99% [-0.53%]
Competitiveness(Normalized) Mean: Third Choices	0.9598 [0.0409]	1.0195 [0.0564]	1.1032 [0.0645]	1.3041 [0.0626]
Distance(Normalized) Mean: Third Choices	-0.3201 [-0.0201]	-0.1863 [0.0127]	-0.1141 [-0.0145]	0.0592 [0.0263]
STEM Concentration Share: Third Choices	41.78% [-0.1%]	40.58% [-6.55%]	40.44% [-1.84%]	38.39% [0.91%]
Finance Concentration Share: Third Choices	9.5% [0.5%]	9.4% [-0.37%]	9.25% [0.27%]	9.34% [0.29%]
Medical School Share: Third Choices	9.06% [-0.32%]	6.73% [0.06%]	5.23% [-0.53%]	3.36% [-0.56%]
Competitiveness(Normalized) Mean: Fourth Choices	0.7293 [0.0657]	0.7723 [0.088]	0.8496 [0.0657]	1.0278 [0.0468]
Distance(Normalized) Mean: Fourth Choices	-0.4108 [0.0267]	-0.2956 [0.0262]	-0.2228 [-0.0462]	-0.0546 [-0.0666]
STEM Concentration Share: Fourth Choices	37.27% [-3.94%]	36.38% [-6.03%]	35.72% [-4.79%]	34.33% [-4.06%]
Finance Concentration Share: Fourth Choices	9.2% [0.73%]	9.76% [-1.15%]	9.95% [-0.42%]	10.37% [3.03%]
Medical School Share: Fourth Choices	11.82% [0.65%]	8.78% [-0.55%]	7.33% [-0.09%]	4.36% [-1.42%]

Note: This table presents details of the fit of mixture model in Section 7.4 and Table 4. The predicted value are calculated using the science-track student whose score is between 80th and 100th percentile among elite college eligible applicants. Prediction error, as defined by predicted value minus the value of moments, are in squared brackets.

C Additional Results and Details bout Structural Estimation

C.1 Specification

This section lays out the details on the specification and the moments we use for the structural estimation in Section 7.

Remember in in the mixture model there are two types of decision maker, the Rational Type and the DC Type. We will use superscript RN to declare that the parameter is only relevant for the Rational Type, and DC to declare that the parameter is only relevant for the DC Type.

Remember in Section 7.2 we state that the utility specification we use is:

$$u_{ij} = f(\theta_i^C, C_{ij}, SES_i) + g(\theta_i^d, d_j, SES_i) + h(\theta_i^X, X_j, SES_i) + O_i + \epsilon_{ij}$$

In the benchmark mixture model (Table 4, parameters differ across types. Below we detail the specification we use for each type, for student i and college j:

$$u_{ij}^{RN} = f_{ij}^{RN} + g_{ij}^{RN} + h_{ij} + O^{RN} + \epsilon_{ij}$$

$$u_{ij}^{DC} = f_{ij}^{DC} + g_{ij}^{DC} + h_{ij} + O^{DC} + \epsilon_{ij}$$

where $\epsilon \sim N(0, \sigma_\epsilon^2)$, with σ_ϵ being the same across types.

Details of f_{ij}^{RN} and f_{ij}^{DC} First let's discuss the details of f_{ij}^{RN} and f_{ij}^{DC}. The specification for f_{ij}^{RN} is

$$f_{RN} = \frac{C_j^{1-\theta_i^C} - 1}{1 - \theta_i^C}$$

Let NC_j denote the normalized average cutoffs in 2014-2018 for college j. Then $C_j \equiv 10 * (NC_j - min_{j \in \textbf{ elite college}}\{NC_j\})$ to ensure that C_j is non-negative. And

$$\theta_i^C \sim N(\mu_C^{RN} + \mu_\beta^{RN} SES_i, (\sigma_C^{RN})^2)$$

Similarly, for the DC Type we have

$$f_{DC} = \frac{C_j^{1-\theta_i^C} - 1}{1 - \theta_i^C}$$

$$\theta_i^C \sim N(\mu_C^{DC} + \nu_C^{DC} SES_i, (\sigma_C^{DC})^2)$$

Details of g_{ij}^{RN} and g_{ij}^{DC} We next discuss the details of g_{ij}^{RN} and g_{ij}^{DC}. For g_{ij}^{RN} we have,

$$g_{ij}^{RN} = \theta_i^d (d_j, d_j^2)'$$

where $\theta_i^d = (\theta_i^{d1}, \theta_i^{d2})$, and the distribution of linear coefficient is assumed to be the same across types to make the utility across types of similar scales:

$$\theta_i^{d1} \sim N(\mu_{d1} + \nu_{d1} SES_i, (\sigma_{d1})^2)$$

the distribution of quadratic coefficient is allowed to be different across types. For the Rational Type we have:

$$\theta_i^{d2} \sim N(\mu_{d2}^{RN} + \nu_{d2}^{RN} SES_i, (\sigma_{d1}^{RN})^2)$$

For the DC Type we have:

$$\theta_i^{d2} \sim N(\mu_{d2}^{DC} + \nu_{d2}^{DC} SES_i, (\sigma_{d2}^{DC})^2)$$

Details of h_{ij} Lastly, we discuss h_{ij}. X_j contains three variables: whether the college is a Science&Technology oriented college X_j^{STEM}, whether the college is a Finance oriented college X_j^{FIN}, and whether the college is a Medical School X_j^{MED}. These categories are mutually exclusive. h_{ij} is

$$h_{ij} = \theta_i^{X,STEM} X_j^{STEM} + \theta_i^{X,FIN} X_j^{FIN} + \theta_i^{X,MED} X_j^{MED}$$

where

$$\theta_i^{X,STEM} \sim N(\mu^{X,STEM} + \nu^{X,STEM} SES_i, (\sigma_{X,STEM})^2)$$

$$\theta_i^{X,FIN} \sim N(\mu^{X,FIN} + \nu^{X,FIN} SES_i, (\sigma^{X,FIN})^2)$$

$$\theta_i^{X,MED} \sim N(\mu^{X,MED} + \nu^{X,MED} SES_i, (\sigma^{X,MED})^2)$$

The probability of being

$$P(\text{DC Type}|\text{SES}_i) = \frac{exp(\gamma_0 + \gamma_1 * SES_i)}{1 + exp(\gamma_0 + \gamma_1 * SES_i)}$$

C.2 Subjective Beliefs

Evidence from Survey A number of recent studies have (Kapor et al., 2020; Arteaga et al., 2021) documented that students may not accurately estimate the probability of admission, especially when the structure of priority scores is more complicated. While in our context the only uncertainty comes from the variation in cutoffs, a one-dimensional object, it is quite unlikely that students' beliefs are perfectly accurate. We elicited students' beliefs regarding the unconditional probability of the four colleges on their lists, and compare the elicited beliefs to the estimated probability that we construct. Subjective beliefs are positively correlated with estimated probability, at a correlation of 0.50. We define belief error as the difference between subjective beliefs and estimated probability, and regress the error on students' socioeconomic index, controlling for other variables including priority score and college preferences. As demonstrated in Table B6, students on average overestimate the chance of admission by 12.1%, and the mean of absolute error is 31.0%.

Despite substantial differences in contexts, the level of these statistics are not far from estimates in Kapor et al. (2020). While socioeconomically advantaged students seem to be somewhat more optimistic, 1 SD of increase in SES is associated with less than 1.85% increase in subjective beliefs. The estimated mean of absolute error is also slightly larger among the advantaged (Column 3 and 4), but the magnitude is also small (1 SD of increase in SES is associated with around 1% increase in absolute errors). Taken together, the belief data suggests that belief errors, while substantial, is at best weakly correlated with the demographics.

Accounting for Heterogeneous Beliefs in Structural Estimation The specification of the perceived probability admission of college j for student i is:

$$p_{ij} = max\{0, min\{1, \hat{p_{ij}} + \tau_{ij}\}\}$$

where $\tau_{ij} \sim N(\mu_{\tau 0} + \mu_{\tau 1}\text{SES}_i, exp(\mu_{\tau 2} + \mu_{\tau 3}\text{SES}_i)^2)$. $\mu_{\tau 0} + \mu_{\tau 1}\text{SES}_i$ dictates student i's overall optimism; $exp(\mu_{\tau 2} + \mu_{\tau 3}\text{SES}_i)^2$ dictates the standard deviation of student i's idiosyncratic beliefs about admission probability on top of the student's overall optimism. In the estimation, we calibrate the parameter by referring to the estimation results from survey. Specifically, the value of $\mu_{\tau 0} = 12.1\%$ and $\mu_{\tau 1} = 1.85\%$ is taken from results in Table B6. $\mu_{\tau 2} = -0.889$ and $\mu_{\tau 3} = 0$ is based on the variance of beliefs and the finding that belief error in its square term does not change in a quantitatively significant way across students of different SES status.

In Panel B of Table B8, we consider the impact of heterogeneous beliefs about admission probability on our estimation. We re-run the same specifications in Table 4. In terms of fit, the mixture model outperforms the one-type rational model by an even larger margin (54.3%, 85.8%, 93.9% for the 40% $\sim$ 60%, 60% $\sim$ 80%, 80% $\sim$ 100% respectively), with the MMSC-BIC metric favoring the mixture model even more. The fit with heterogeneous beliefs is not as good as our benchmark estimate in Table 4, potentially because our model of belief errors is unable to perfectly capture students' beliefs. Another surprising finding is that the estimated share of the DC Type is more than 90% regardless of the subsample we focus on. The overall overconfidence and substantial idiosyncrasies in beliefs ensure that students have large positive belief errors about many colleges, such that, even if students eliminate the risk by only choosing colleges whose subjective probability is close to 100%, the objective probability may actually be much lower. This is particularly a problem for the rational models, as the first choices under the rational rule are the most preferred, and thus more likely to be the competitive colleges mistakenly chosen due to large positive belief errors.

D Mathematical Proofs

In this section we detail the derivation described in Section 6 and 7. Let's begin with several basic notations.

- For college A, the utility of admission is denoted by u_A. The assignment probability of A given priority score s is denoted by $p_A(s)$. Similarly, the assignment probability of B, C is denoted by $p_B(s)$ and $p_C(s)$ and so on.

For convenience, throughout the derivation outside option $\underline{u}$ is normalized to 0. If a ROL is shorter than 4, it means that students leave the rest of it blank.

Proposition 2 *For a pair of college A, B, if there exists $\delta > 0$ such that $p_A(s) = p_B(s + \delta)$ for any $s \in [\underline{s}, \bar{s}]$ and $p_B(s)$ is continuous and log-concave, then*

$$\frac{p_A(s)}{p_B(s)}$$

is decreasing in s when $s \in [\underline{s}, \bar{s}]$.

Proof. Let

$$g(s) \equiv \frac{p_A(s)}{p_B(s)} = \frac{p_B(s+\delta)}{p_B(s)}$$

We have

$$\text{sgn } g'(s) = \text{sgn } (\frac{p'_B(s+\delta)}{p_B(s+\delta)} - \frac{p'_B(s)}{p_B(s)})$$

As $p_B(.)$ is log-concave, $\frac{d(ln(p_B(x)))}{dx} = \frac{p'_B(x)}{p_B(x)}$ decreases over x.

Thus,

$$g'(s) < 0$$

■

In our setting, as colleges which has comparable competitiveness are assumed to have normally distributed cutoffs with similar dispersion, this lemma becomes applicable when the derivation involves the pairwise ratio of assignment probability.

Several assumptions we often make in derivations are discussed below:

Assumption 1 *For any pair of college X, Y where at least one appears on the list, $u_X \neq u_Y$*

This assumption effectively says that choices matter for students as it rules out indifference among listed colleges.

Assumption 2 *For any pair of college X, Y, there does not exist a pair of priority score s_1 and s_2 such that*

$$sgn((p_X(s_1) - p_Y(s_1)) \neq sgn((p_X(s_2) - p_Y(s_2))$$

This assumption is testable if we regard assignment probability as observables. Intuitively it says that the relationship where X is riskier/safer than Y does not change with one's priority score s. It holds in our setting because cutoffs are assumed to be normally distributed, where those with comparable competitive have similar dispersion in cutoff distribution.

Assumption 3 *for any pairs of college A, B,*

$$\frac{min\{p_A(s), p_B(s)\}}{max\{p_A(s), p_B(s)\}}$$

increases for $s \in [\underline{s}, \bar{s}]$,

This assumption trivially holds if the condition in Proposition 2 holds. Intuitively it says that the assignment probability of the riskier college increases at a faster rate than the safer college, a property that is true for any pair of colleges with log-concave distributions,and similar dispersion of cutoffs.

Important notations before we derive the theorems:

- Let u denote utility vector $(u_1, u_2, .., u_n)$, preferences over colleges.
- The position of a college on the list is encoded by κ. $\kappa = 0$ if the college is omitted from the list; $\kappa = 1$ if the college is listed as the fourth choice; $\kappa = 2$ if the college is listed as the third choice; $\kappa = 3$ if the college is listed as the second choice; $\kappa = 4$ if the college is listed as the first choice.
- Function $\mathcal{R} : (u, A, s) \mapsto \kappa$ maps utility u, college A, priority score s into position κ under Rational Decision Rule.
- Function $\mathcal{D} : (u, A, s) \mapsto \kappa$ maps utility u, college A, priority score s into position κ under DC Decision Rule.
- Set $\mathcal{C}^{RN}_{(u,A,\kappa)} = \{s|\mathcal{R}(u, A, s) = \kappa\}$ is the contour set of priority score s where A is listed as at position κ under Rational Decision Rule and preference u.
- Set $\mathcal{C}^{DC}_{(u,A,\kappa)} = \{s|\mathcal{D}(u, A, s) = \kappa\}$ is the contour set of priority score s where A is listed as at position κ under Rational Decision Rule and preference u.

Proposition 3 *If Assumption 1, 2, 3 hold, for any* $\underline{s} < s < s + \delta < \bar{s}$ *the following three scenarios (forms of upward movement) are impossible under Rational Decision Rule (if length of list is shorter than 4, it means that the rest is left blank):*

1. *Choose* (X, Y) *when priority score is s; choose* (Y, Z) *when priority score is* $s + \delta$*;*
2. *Choose* (X, Y, Z) *when priority score is s; choose* (Y, Z, W) *when priority score is* $s+\delta$*;*
3. *Choose* (X, Y, Z, W) *when priority score is s; choose* (Y, Z, W, M) *when priority score is* $s + \delta$*;*

Proof.

Scenario 1 The optimality implies that

$$p_X(s)u_X + (1-p_X(s))p_Y(s)u_Y \geq p_Y(s)u_Y + (1-p_Y(s))p_Z(s)u_Z$$

and

$$p_X(s+\delta))u_X + (1-p_X(s+\delta)))p_Y(s+\delta))u_Y \leq p_Y(s+\delta))u_Y + (1-p_Y(s+\delta)))p_Z(s+\delta))u_Z$$

Reorganize these two equations we get

$$\frac{p_X(s)}{p_Z(s)} \geq \frac{1-p_Y(s)}{u_X - p_Y(s)u_Y}u_Z$$
$$\frac{p_X(s+\delta)}{p_Z(s+\delta)} \leq \frac{1-p_Y(s+\delta)}{u_X - p_Y(s+\delta)u_Y}u_Z$$

As optimality also requires that $u_X \geq u_Y \geq u_Z$, we know that $p_X(s+\delta) < p_Z(s+\delta)$. Thus,

$$\frac{p_X(s+\delta)}{p_Z(s+\delta)} \geq \frac{min\{p_X(s), p_Z(s)\}}{max\{p_X(s), p_Z(s)\}} = \frac{p_X(s)}{p_Z(s)}$$

On the other hand, $\frac{1-p_Y(s)}{u_X - p_Y(s)u_Y}$ is decreasing in s, which leads to contradiction.

Scenario 2 The optimality implies that

$$p_X(s)u_X + (1-p_X(s))p_Y(s)u_Y + (1-p_X(s))(1-p_Y(s))p_Z(s)u_Z \geq$$
$$p_Y(s)u_Y + (1-p_Y(s))p_Z(s)u_Z + (1-p_Y(s))(1-p_Z(s))p_W(s)u_W$$

and

$$p_X(s+\delta)u_X + (1-p_X(s+\delta))p_Y(s+\delta)u_Y + (1-p_X(s+\delta))(1-p_Y(s+\delta))p_Z(s+\delta)u_Z \leq$$
$$p_Y(s+\delta)u_Y + (1-p_Y(s+\delta))p_Z(s+\delta)u_Z + (1-p_Y(s+\delta))(1-p_Z(s+\delta))p_W(s+\delta)u_W$$

Reorganizing these two equations in a similar way we get

$$\frac{p_X(s)}{p_W(s)} \geq \frac{(1-p_Y(s))(1-p_Z(s))}{u_X - u_Y + (1-p_Y(s))(u_Y - p_Z(s)u_Z)}u_W$$

and

$$\frac{p_X(s+\delta)}{p_W(s+\delta)} \leq \frac{(1-p_Y(s+\delta))(1-p_Z(s+\delta))}{u_X - u_Y + (1-p_Y(s+\delta))(u_Y - p_Z(s+\delta)u_Z)}u_W$$

As $u_X > u_Y > u_Z > u_W$, we have $p_X(s+\delta) < p_W(s+\delta)$. THus,

$$\frac{p_X(s+\delta)}{p_W(s+\delta)} > \frac{min\{p_X(s), p_W(s)\}}{max\{p_X(s), p_W(s)\}} = \frac{p_X(s)}{p_W(s)}$$

On the other hand, we have

$$\frac{(1-p_Y(s))(1-p_Z(s))}{u_X - u_Y + (1-p_Y(s))(u_Y - p_Z(s)u_Z)} = \frac{1}{\frac{u_X-u_Y}{(1-p_Y(s))(1-p_Z(s))} + \frac{u_Y-p_Z(s)u_Z}{1-p_Z(s)}}$$

where the first term of the denominator is positive and increasing in s, and the second term is also increasing in s per derivation in Scenario 1. Thus $\frac{(1-p_Y(s))(1-p_Z(s))}{u_X-u_Y+(1-p_Y(s))(u_Y-p_Z(s)u_Z)}$ is decreasing in s, which leads to contradiction.

Scenario 3 Similar to the manipulation above, we obtain

$$\frac{p_X(s)}{p_M(s)} \geq \frac{(1-p_Y(s))(1-p_Z(s))(1-p_W(s))}{u_X - u_Y + (1-p_Y(s))[u_Y - u_Z + (1-p_Z(s))(u_Z - p_W(s)u_W)]}u_M$$

and

$$\frac{p_X(s+\delta)}{p_M(s+\delta)} \leq \frac{(1-p_Y(s+\delta))(1-p_Z(s+\delta))(1-p_W(s+\delta))}{u_X - u_Y + (1-p_Y(s+\delta))[u_Y - u_Z + (1-p_Z(s+\delta))(u_Z - p_W(s+\delta)u_W)]}u_M$$

Since

$$\frac{(1-p_Y(s))(1-p_Z(s))(1-p_W(s))}{u_X - u_Y + (1-p_Y(s))[u_Y - u_Z + (1-p_Z(s))(u_Z - p_W(s)u_W)]} = \frac{1}{\frac{u_X-u_Y}{(1-p_Y(s))(1-p_Z(s))(1-p_W(s)} + \frac{u_Y-u_Z+(1-p_Z(s+\delta))(u_Z-p_W(s+\delta)u_W)}{(1-p_Z(s))(1-p_W(s))}}$$

where the first term of denominator is increasing in s, and the second term is as well per derivation in Scenario 2. Thus $\frac{(1-p_Y(s))(1-p_Z(s))(1-p_W(s))}{u_X-u_Y+(1-p_Y(s))[u_Y-u_Z+(1-p_Z(s))(u_Z-p_W(s)u_W)]}u_M$ is decreasing s, which leads to contraction.

■

Proposition 4 *If Assumption 1, 2, 3 hold, and $\mathcal{R}(u, A, s) \geq 1$, then for any s and $\delta > 0$, $\mathcal{R}(u, A, s) \geq \mathcal{R}(u, A, s+\delta)$ or $\mathcal{R}(u, A, s+\delta) = 0$.*

Proof. It suffices to show that $1 \leq \mathcal{R}(u, A, s+\delta) < \mathcal{R}(u, A, s)$ would lead to contradiction. Namely, it is impossible that college A is selected and appears at a lower position when priority score is lower. Below we show that this would lead to contradiction in every possible scenario.

Scenario 1 There exists a college Y such that $\mathcal{R}(u, Y, s) = 4$ and $\mathcal{R}(u, Y, s+\delta) = 3$

To prove by contradiction, suppose the optimal list is (X, Y, V, W) when priority score is s and the optimal list is (Y, Z, M, N) when priority score is $s+\delta$, where M, N, V, W are just other colleges that could be identical or different. Let $U_{(M,N)}(s)$ and $U_{(V,W)}(s)$ denote the expected utility of sub-portfolio (M, N), (V, W) when priority score is s respectively.

X and Z cannot be the same college, which leads to contradiction immediately. The optimality implies that

$$\begin{aligned}p_X(s)u_X + (1 - p_X(s))p_Y(s)u_Y + (1 - p_X(s))(1 - p_Y(s))U_{(M,N)} \geq \\ p_Y(s)u_Y + (1 - p_Y(s))p_Z(s)u_Z + (1 - p_Y(s))(1 - p_Z(s))U_{(M,N)}\end{aligned}$$

Similarly,

$$\begin{aligned}p_X(s+\delta)u_X + (1 - p_X(s+\delta))p_Y(s+\delta)u_Y + (1 - p_X(s+\delta))(1 - p_Y(s+\delta))U_{(V,W)} \geq \\ p_Y(s+\delta)u_Y + (1 - p_Y(s+\delta))p_Z(s+\delta)u_Z + (1 - p_Y(s+\delta))(1 - p_Z(s+\delta))U_{(V,W)}\end{aligned}$$

Reorganizing these two inequalities, we have

$$\frac{p_X(s)}{p_Z(s)} \geq \frac{(1 - p_Y(s))u_Z - (1 - p_Y(s))U_{(M,N)}(s)}{u_X - p_Y(s)u_Y - (1 - p_Y(s))U_{(M,N)}(s)}$$

and

$$\frac{p_X(s+\delta)}{p_Z(s+\delta)} \leq \frac{(1 - p_Y(s+\delta))u_Z - (1 - p_Y(s+\delta))U_{(V,W)}(s+\delta)}{u_X - p_Y(s+\delta)u_Y - (1 - p_Y(s+\delta))U_{(V,W)}(s+\delta)}$$

The optimality implies that $u_X > u_Y > u_Z$. This in turn implies that $p_X(s) < p_Z(s)$, because otherwise it is never optimal to list (Y, Z) as top two choices. When $V \neq Z$ and $W \neq Z$, $U_{(V,W)}$ cannot be larger than $U_{(M,N)}$, because this would imply that (V, W) is a better sub-portfolio than (M, N) when priority score is s. Thus,

$$\frac{p_X(s)}{p_Z(s)} < \frac{p_X(s+\delta)}{p_Z(s+\delta)}$$

However, we have

$$\begin{aligned}&\frac{(1 - p_Y(s+\delta))u_Z - (1 - p_Y(s+\delta))U_{(V,W)}(s+\delta)}{u_X - p_Y(s+\delta)u_Y - (1 - p_Y(s+\delta))U_{(V,W)}(s+\delta)} \\ \leq\ &\frac{(1 - p_Y(s+\delta))u_Z - (1 - p_Y(s+\delta))U_{(M,N)}(s+\delta)}{u_X - p_Y(s+\delta)u_Y - (1 - p_Y(s+\delta))U_{(M,N)}(s+\delta)} \\ <\ &\frac{(1 - p_Y(s+\delta))(u_Z - U_{(M,N)}(s))}{u_X - p_Y(s+\delta)u_Y - (1 - p_Y(s+\delta))U_{(M,N)}(s)} \\ <\ &\frac{(1 - p_Y(s))(u_Z - U_{(M,N)}(s))}{u_x - p_Y(s)u_y - (1 - p_Y(s))U_{(M,N)}(s)}\end{aligned}$$

which leads to contradiction.

When $V = Z$, the list is (X, Y, Z, W) when priority score is s and (Y, Z, M, N) when priority score is $s+\delta$. The optimality condition thus implies that $(X, Y, Z, W) \succ (Y, Z, M, W)$ when priority score is s, $(Y, Z, M, N) \succ (X, Y, Z, N)$ when priority score is $s + \delta$. In this case let $U_N(s)$, $U_W(s)$ denote the expected utility of N and W when priority score is s respectively. We have $U_W(s) \leq U_N(s) < u_M$, as otherwise n would be suboptimal when score is s. From the preference ordering above (after similar algebraic manipulations) we have,

$$\frac{p_X(s)}{p_M(s)} \geq \frac{(1-p_Y(s))(1-p_Z(s))(u_M - U_W(s))}{u_X - u_Y + (1-p_Y(s))[u_Y - p_Z(s)u_Z - (1-p_z(s))U_W(s)]}$$

and

$$\frac{p_X(s+\delta)}{p_M(s+\delta)} \leq \frac{(1-p_Y(s+\delta))(1-p_Z(s+\delta))(u_M - U_N(s+\delta))}{u_X - u_Y + (1-p_Y(s+\delta))[u_Y - p_Z(s+\delta)u_Z - (1-p_z(s+\delta))U_N(s+\delta)]}$$

Since $u_X > u_Y > u_Z > max\{u_W, u_M, u_N\}$, we have $p_X(s) < p_M(s)$. Thus $\frac{p_X(s+\delta)}{p_M(s+\delta)} > \frac{p_X(s)}{p_M(s)}$. Also the expression on the right is decreasing in U, thus

$$\begin{aligned}
&\frac{(1-p_Y(s))(1-p_Z(s))(u_M - U_W(s))}{u_X - u_Y + (1-p_Y(s))[u_Y - p_Z(s)u_Z - (1-p_z(s))U_W(s)]} \\
&\geq \frac{(1-p_Y(s))(1-p_Z(s))(u_M - U_N(s+\delta))}{u_X - u_Y + (1-p_Y(s))[u_Y - p_Z(s)u_Z - (1-p_z(s))U_N(s+\delta)]} \\
&\geq \frac{(1-p_Y(s+\delta))(1-p_Z(s+\delta))(u_M - U_N(s+\delta))}{u_X - u_Y + (1-p_Y(s+\delta))[u_Y - p_Z(s+\delta)u_Z - (1-p_z(s+\delta))U_N(s+\delta)]}
\end{aligned}$$

which leads to contradiction.

When $W = Z$, the list is (X, Y, V, Z) when priority score is s, and (Y, Z, M, N) when priority score is $s+\delta$. Optimality implies that $(V, Z) \succ (Z, M)$ when priority score is s, and $(Z, M, N) \succ (V, Z, N)$ when priority score is $s + \delta$. Mathematically, the latter is equivalent to

$$\begin{aligned}
&p_Z(s+\delta)u_Z + (1-p_Z(s+\delta))p_M(s+\delta)u_M + (1-p_Z(s+\delta))(1-p_M(s+\delta))p_N(s+\delta)u_N \geq \\
&\quad p_V(s+\delta)u_V + (1-p_V(s+\delta))p_Z(s+\delta)u_Z + (1-p_V(s+\delta))(1-p_Z(s+\delta))p_N(s+\delta)u_N
\end{aligned}$$

Since optimality also implies $u_X > u_Y > u_V > u_Z > u_M > u_N$, it implies that $p_M(s+\delta) > p_V(s+\delta)$. Thus $(Z, M, N) \succ (V, Z, N)$ implies that

$$p_Z(s+\delta)u_Z + (1-p_Z(s+\delta))p_M(s+\delta)u_M \geq p_V(s+\delta)u_V + (1-p_V(s+\delta))p_Z(s+\delta)u_Z$$

which is equivalent to $(z, m) \succ (v, z)$. As Proposition 3 has proved, this choice pattern cannot be generated by the rational type.

Proof of Scenario 1 concludes.

Scenario 2 There exists a college Y such that $\mathcal{R}(u, Y, s) = 2$ $\mathcal{R}(u, Y, s+\delta) = 3$ and

In other words, a rational type chooses (V, X, Y, W) when priority score is s, chooses (M, Y, Z, N) when priority score is $s + \delta$. When $W \neq Z$, the analysis of this case becomes essentially the same as Scenario 1.

When $W = Z$, $M \geq X$ because the choice pattern otherwise has been proved to be impossible in Proposition 3. Thus the scenario implies that $(X, Y, Z) \succ (Y, Z, N)$ when priority score is s, but $(Y, Z, N) \succ (X, Y, Z)$ when priority score is $s + \delta$, an impossible pattern again according to Proposition 3.

Proof of Scenario 2 concludes.

Scenario 3 There exists a college Y such that $\mathcal{R}(u, Y, s) = 1$ and $\mathcal{R}(u, Y, s+\delta) = 2$ and

In other words, a rational type chooses (V, W, X, Y) when priority score is s, (M, N, Y, Z) when priority score is $s + \delta$. If $M \neq X$ and $N \geq X$, the optimality condition requires that $(X, Y) \succ (Y, Z)$ when score is s, but $(Y, Z) \succ (X, Y)$ when score is $s + \delta$, which according to Proposition 3 are impossible to hold at the same time.

If $N = X$, $M \neq W$ because of proposition 3. Consequently, $(W, X, Y) \succ (X, Y, Z)$ when score is s, $(X, Y, Z) \succ (W, X, Y)$ when score is $s+\delta$, again impossible thanks to Proposition 3.

If $M = X$, a rational type chooses (V, W, X, Y) when priority score is s, (X, N, Y, Z) when priority score is $s + \delta$. The optimality requires that when score is s, $(W, X, Y) \succ (X, N, Y)$, which is equivalent to

$$p_W(s)u_W + (1 - p_W(s))p_X(s)u_X + (1 - p_W(s))(1 - p_X(s))p_Y(s)u_Y >$$
$$p_X(s)u_X + (1 - p_X(s))p_N(s)u_N + (1 - p_X(s))(1 - p_N(s))p_Y(s)u_Y$$

The optimality also implies that $u_V > u_W > u_X > u_N > u_Y > u_Z$, and consequently $max\{p_V, p_W\} < min\{p_X, p_Y, p_N, p_Z\}$. As a result, we can infer that $(1-p_W(s)) > (1-p_N(s))$, and consequently $(W, X, Y, Z) \succ (X, N, Y, Z)$ when score is s.

Together with $(X, N, Y, Z) \succ (W, X, Y, Z)$ when score is $s + \delta$, this scenario can be dealt with using the derivation in Scenario 1.

Proof of Scenario 3 concludes.

Scenario 4 There exists college Y such that $\mathcal{R}(u, Y, s) = 2$ and $\mathcal{R}(u, Y, s + \delta) = 4$.

In other words, the optimal list is (X, V, Y, W) when score is s, (Y, M, Z, N) when score is $s+\delta$. The optimality condition implies that $u_X > u_V > u_Y > u_M > u_Z > u_N$ and $u_Y > u_W$, $max\{p_X, p_W\} < min\{p_Y, p_M, p_Z, p_N\}$.

When score is $s + \delta$, we have $(Y, M, Z, N) \succ (V, Y, Z, N)$. Mathematically,

$$p_Y(s+\delta)u_Y + (1 - p_Y(s+\delta))p_M(s+\delta)u_M + (1 - p_Y(s+\delta))(1 - p_M(s+\delta))EU[(Z, N)] >$$
$$p_V(s+\delta)u_V + (1 - p_V)(s+\delta)p_Y(s+\delta)u_Y + (1 - p_V(s+\delta))(1 - p_Y(s+\delta))EU[(Z, N)]$$

where $EU[(Z,N)] \equiv= p_Z(s+\delta)u_Z + (1-p_Z(s+\delta))p_N(s+\delta)u_N$.

If $W \neq M$, the optimality condition when score is $s+\delta$ implies that $(Z,N) \succ (W)$, which is equivalent to $EU[(Z,N)] > EU[(W)] \equiv p_W(s+\delta)u_W$. As $(1-p_M) < (1-p_V)$, we have

$$p_Y(s+\delta)u_Y + (1-p_Y(s+\delta))p_M(s+\delta)u_M + (1-p_Y(s+\delta))(1-p_M(s+\delta))EU[(W)] >$$
$$p_V(s+\delta)u_V + (1-p_V(s+\delta))p_Y(s+\delta)u_Y + (1-p_V(s+\delta))(1-p_Y(s+\delta))EU[(W)]$$

which implies $(Y,M,W) \succ (V,Y,W)$ when score is $s+\delta$. On the other hand, $(V,Y,W) \succ (Y,M,W)$ when is score s. As shown in Scenario 1, this is impossible.

If $W = M$, the optimal list is (X,V,Y,W) when score is s, (Y,W,Z,N) when score is $s+\delta$. In this case all the other colleges have to be different from each other: $u_X > u_V > u_Y > u_W > u_Z > u_N$. This in turn implies that $max\{p_X,p_V\} < min\{p_Y,p_Z,p_N,p_W\}$. The optimality condition when score is s implies that $(V,Y,W) \succ (Y,Z,N)$. The optimality condition when score is $s+\delta$ implies that $(Y,W,Z,N) \succ (V,Y,W,N)$. Mathematically:

$$EU[(Y,W,Z)] + (1-p_Y(s+\delta))(1-p_W(s+\delta))(1-p_Z(s+\delta))p_N(s+\delta)u_N \geq$$
$$EU[(V,Y,W)] + (1-p_V(s+\delta))(1-p_Y(s+\delta))(1-p_W(s+\delta))p_N(s+\delta)u_N$$

where $EU[(Y,W,Z)] \equiv p_Y(s+\delta)u_Y + (1-p_Y(s+\delta))p_W(s+\delta)u_W + (1-p_Y(s+\delta))(1-p_W(s+\delta))p_Z(s+\delta)u_Z$, $EU[(V,Y,W)] \equiv p_V(s+\delta)u_V + (1-p_V(s+\delta))p_Y(s+\delta)u_Y + (1-p_V(s+\delta))(1-p_Y(s+\delta))p_W(s+\delta)u_W$ As $(1-p_Z(s+\delta)) < (1-p_V(s+\delta))$, we have $EU[(Y,W,Z)] > EU[(V,Y,W)]$, which implies that $(Y,W,Z) \succ (V,Y,W)$ when score is $s+\delta$. Impossible according to Proposition 2.

Proof of Scenario 4 concludes.

Scenario 5 There exists a college Y such that $\mathcal{R}(u,Y,s) = 1$ and $\mathcal{R}(u,Y,s+\delta) = 3$

In other words, the optimal list is (X,V,W,Y) when score is s, (M,Y,Z,N) when score is $s+\delta$. The optimality condition requires that $u_X > u_V > u_W > u_Y > u_Z > u_N$ and $u_M > u_Y$. This in turn implies that $max\{p_X,p_V,p_W\} < min\{p_M,p_Y,p_Z,p_N\}$. If all the letters here denote different colleges, the optimality condition implies that $(Y,Z,N) \succ (W,Y,N)$ when score is $s+\delta$. As $(1-p_Z) < (1-p_W)$, we have $(Y,Z) \succ (W,Y)$ when score is $s+\delta$. When score is s, however, we have $(W,Y) \succ (Y,Z)$, which is impossible according to Proposition 3.

If some letters denote the same college, the only possibility is that M could be X, V or W. If $M = X$ or $M = V$, the same derivation can be applied as well. If $M = W$, the optimal list is (W,Y,Z,N) when score is s, and (X,V,W,Y) when score is s', which appears to be the same Scenario 4.

Proof of Scenario 5 concludes.

Scenario 6 There exists college Y such that $\mathcal{R}(u,A,s) = 1$ and $\mathcal{R}(u,Y,s+\delta) = 4$.

In other words, the optimal list is (Y,M,N,L) when score is $s+\delta$, (W,V,X,Y) when score is s. The optimality condition implies that $u_W > u_V > u_X > u_Y > u_M > u_N > u_L$, and $max\{p_W,p_V,p_X\} < min\{p_M,p_N,p_L,p_Y\}$. As (W,V,X,Y) is the optimal list when score is s, $(X,Y) \succ (Y,M)$ when score is s.

Moreover, as the optimality list is (Y, M, N, L) when score is $s+\delta$. We have $(Y, M, N, L) \succ (X, Y, N, L)$ when score is $s+\delta$. Mathematically this is equivalent to

$$p_Y(s+\delta)u_Y + (1-p_Y(s+\delta))p_M(s+\delta)u_M + (1-p_Y(s+\delta))(1-p_M(s+\delta))EU[(N,L)] \geq$$
$$p_X(s+\delta)u_X + (1-p_X(s+\delta))p_Y(s+\delta)u_Y + (1-p_X(s+\delta))(1-p_Y(s+\delta))EU[(N,L)]$$

where $EU[(N,L)] \equiv p_N(s+\delta)u_N + (1-p_N(s+\delta))p_L(s+\delta)u_L$ As $(1-p_M(s+\delta)) < (1-p_X(s+\delta))$, we have

$$p_Y(s+\delta)u_Y + (1-p_Y(s+\delta))p_M(s+\delta)u_M \geq p_X(s+\delta)u_X + (1-p_X(s+\delta))p_Y(s+\delta)u_Y$$

which is equivalent to $(Y, M) \succ (X, Y)$. This pattern has been proved to be impossible in Proposition 2.

Proof of Scenario 6 concludes.

■

Proposition 5 *Under Assumption 1, 2, 3, for any preference profile u, college A,* $\mathcal{C}^{RN}_{(u,A,\kappa)} \equiv \{s|\mathcal{R}(u, A, s) = \kappa\}$ *is connected if* $\kappa \geq 1$.

Proof.

Scenario 1 $\kappa = 4$

It suffices to show that if college X is listed in a specific position when priority score is $\bar{s}$ and $\underline{s}$, then it is the best candidate for that position as well for any s such that $\underline{s} < s < \bar{s}$. Mathematically

For any college $Y \neq X$, we have

$$p_Y(\bar{s})u_Y + (1-p_Y(\bar{s}))U(\bar{s}) \leq p_X(\bar{s})u_X + (1-p_X(\bar{s}))U(\bar{s})$$

$$p_Y(\underline{s})u_Y + (1-p_Y(\underline{s}))U(\underline{s}) \leq p_X(\underline{s})u_X + (1-p_X(\underline{s}))U(\underline{s})$$

where $U(s)$ represent the utility of the list of colleges chosen below the current position when priority score is s. Since $\underline{s} < s < \bar{s}$, we have $U(\underline{s}) \geq U(s) \geq U(\bar{s})$. Importantly, note that this holds because X cannot be any of the non-top choices $(1 \leq \mathcal{R}(u, X, s) < 4)$ when $s \in [\underline{s}, \bar{s}]$ thanks to Proposition 3.

The two equations above are equivalent to

$$\frac{p_X(\bar{s})}{p_Y(\bar{s})} \geq \frac{u_Y - U(\bar{s})}{u_X - U(\bar{s})}$$

$$\frac{p_X(\underline{s})}{p_Y(\underline{s})} \geq \frac{u_Y - U(\underline{s})}{u_X - U(\underline{s})}$$

Next we show that it is true that

$$\frac{p_X(s)}{p_Y(s)} \geq \frac{u_Y - U(s)}{u_X - U(s)}$$

We analyze whether X is a better choice when probability is $p_X(s)$, case by case.

Case (I): $p_X > p_Y$, $u_X < u_Y$. In this case we have

$$\frac{p_X(s)}{p_Y(s)} \geq \frac{p_X(\bar{s})}{p_Y(\bar{s})} \geq \frac{u_Y - U(\bar{s})}{u_X - U(\bar{s})} \geq \frac{u_Y - U(s)}{u_X - U(s)}$$

Case (II): $p_X < p_Y$, $u_X > u_Y$. In this case we have

$$\frac{p_X(s)}{p_Y(s)} \geq \frac{p_X(\underline{s})}{p_Y(\underline{s})} \geq \frac{u_Y - U(\underline{s})}{u_X - U(\underline{s})} \geq \frac{u_Y - U(s)}{u_X - U(s)}$$

Case (III): $p_X > p_Y$, $u_X > u_Y$, obviously X is better regardless of probability.

Case (IV): $p_X < p_Y$, $u_X < u_Y$, Y must be chosen regardless of probability, which leads to contradiction.

Proof of Scenario 1 concludes.

Scenario 2 $\kappa \leq 3$

The proof of Scenario 1 can be largely recycled, with the only complication being whether X could be in a position where $\mathcal{R}(u, X, s) > \kappa$. This is again impossible thanks to Proposition 3.

■

Remark Proposition 3 and 4 together imply Theorem 1.

Proposition 6 *Suppose Assumption 1, 2, 3 hold, and that the tie of expected utility among listed colleges is limited to at most two colleges. For any u and A, if there exists $\underline{s} < \bar{s}$ such that $\mathcal{D}(u, A, \underline{s}) = 0$ and $\mathcal{D}(u, A, \bar{s}) = \kappa \geq 2$, then there exists $\underline{s} < s < \bar{s}$ such that $1 \leq \mathcal{D}(u, A, s) \leq \kappa - 1$.*

Proof. Let $f_A(s) = p_A(s)u_A$. $f_A(s)$ is continuous for any college A. Thus for any pairs of A, X, function $\Delta_{AX}(s) \equiv f_A(s) - f_X(s)$ is continuous. Under the assumptions, $\Delta_{AX}(s)$ switches signs at most once. If $p_A(s) > p_X(s)$, it can possibly switch from positive to negative; it $p_X(s) > p_A(s)$, it can possibly switch from negative to positive.

Define $s_4 \equiv sup_s\{s|\mathcal{D}(u, A, s) = 0\}$. According to the continuity we know that there exists college B such that $\Delta_{AB}(s_4) = 0$. This college must be listed at the fourth place, and $\Delta_{AB}(s_4)$ is switching from negative to positive, because otherwise given the assumptions A will not be moved in the neighborhood of s_4. Thus $\mathcal{D}(u, A, s) = 1$ in the neighborhood of s_4.

If $\kappa = 3$, the key is to consider $s_2 \equiv sup_s\{s|\mathcal{D}(u, A, s) > 1\}$. We can infer using the same method that when s is in the neighborhood of s_2, $\mathcal{D}(u, A, s) = 2$.

If $\kappa = 4$, the key is to consider $s_3 \equiv sup_s\{s|\mathcal{D}(u, A, s) > 2\}$. We can infer using the same method that when s is in the neighborhood of s_3, $\mathcal{D}(u, A, s) = 3$.

■

Remark Proposition 6 implies Theorem 2.

Proposition 7 *In the setting as detailed in Section 7.1, we have:*

- *For Rational Decision Rule:*
  1. *When $\delta > 2$, the optimal list is $(B1, B2)$ if $\frac{p_A}{p_B} < \frac{1-p_B}{\delta-2p_B}$; the optimal list is $(A1, B1)$ if $\frac{1-p_B}{\delta-2p_B} < \frac{p_A}{p_B} < \frac{2}{\delta}$; the optimal list is $(A1, A2)$ if $\frac{p_A}{p_B} > \frac{2}{\delta}$.*
  2. *When $1 < \delta < 2$, the optimal list is $(B1, B2)$ if $\frac{p_A}{p_B} < \frac{1}{\delta}$; the optimal list is $(B1, A1)$ if $\frac{p_A}{p_B} > \frac{1}{\delta}$.*
  3. *When $\delta < 1$, the optimal list is $(B1, B2)$.*
- *For the DC Decision Rule:*
  1. *When $\delta > 2$, the optimal list is $(B1, B2)$ if $\frac{p_A}{p_B} < \frac{1}{\delta}$; $(B1, A1)$ if $\frac{1}{\delta} < \frac{p_A}{p_B} < \frac{2}{\delta}$; $(A1, A2)$ if $\frac{p_A}{p_B} > \frac{2}{\delta}$;*
  2. *When $1 < \delta < 2$, the optimal list is $(B1, B2)$ if $\frac{p_A}{p_B} < \frac{1}{\delta}$; $(B1, A1)$ if $\frac{p_A}{p_B} > \frac{1}{\delta}$;*
  3. *When $\delta < 1$, the optimal list is $(B1, B2)$.*

Proof. The expected utility of $(A1, A2)$ is

$$(2p_A - p_A^2)\delta$$

The expected utility of $(A1, B1)$ is

$$p_A\delta + 2(1 - p_A)p_B$$

The expected utility of $(B1, B2)$ is

$$3p_B - p_B^2$$

Thus we have,

$$(A1, B1) \succ (B1, B2) \iff \frac{p_A}{p_B} > \frac{1-_B}{\delta - 2p_B}$$

$$(A1, A2) \succ (A1, B1) \iff \frac{p_A}{p_B} > \frac{2}{\delta}$$

$$(A1, A2) \succ (B1, B2) \iff \frac{p_A}{p_B} > \frac{3 - P_B}{2 - P_A}\frac{1}{\delta}$$

$$(B1, A1) \succ (B1, B2) \iff \frac{p_A}{p_B} > \frac{1}{\delta}$$

■

Remark Proposition 7 provides the intermediate results for Theorem 1.

E Additional Institutional Details

E.1 College Application

The admission process is stratified according to college quality. Before 2019, the colleges were classified into three tiers of decreasing quality: elite (first-tier), public non-elite (second-tier) and private non-elite (third-tier). The latter two categories merged starting in 2019, but the elite category remains unchanged. In this paper, we focus on the admission to elite colleges, which are argued to play a central role in upward mobility in China because of the tremendous value placed on education and the huge return in labor markets (Jia and Li, 2016).

The share of students who are eligible for 1st-tier colleges is roughly $20 \sim 25\%$ of the exam takers. The eligible students on the science track can choose up to four colleges from among 239 elite colleges. For those who are on the humanities track, the total number of elite colleges is 150. Science track students account for more than 80% of the first-tier applicants.

E.2 Priority Score

The priority score is almost completely determined by the College Entrance Exam (CEE)[33]. The CEE is a nationwide closed-book written exam held once a year on June 7th and 8th, with the rare exception that the exam was postponed to July 7th and 8th in 2020 due to COVID-19. To apply for colleges in an admission cycle, all students must take the CEE of the same cycle. In each province, students on the same track (Humanities or Sciences) will take the same exam.[34] As demonstrated in Figure A1, it will take up to two weeks for Ningxia Provincial Education Authorities to grade students' exams. Students will be notified of their exam score and ranking in Ningxia around the 20th-25th of the month in which the exam takes place.

Exams for both tracks include Chinese, Mathematics[35] and English. For each of these subjects, students get an integer score, with the maximum (best) possible being 150 and the minimum being 0. Additionally, students on the Humanities Track take a comprehensive exam on history, politics, and geography, whereas students on the Sciences Track take another exam on physics, chemistry, and biology. This track-specific exam accounts for 300 points. Thus the total score of the CEE (sum of the scores from the four subjects) is 750 points. In case of a tie in total score, ranking will be determined by the score in the comprehensive exam in the respective track, Mathematics, and English, in a lexicographic way.

E.3 Correlation in Admission Events

If the probability of meeting the cutoff of one college is correlated with meeting that of another, our assumptions about independence are defied. In this case, assuming indepen-

[33]Exceptions include winners of international Olympiad contests, students who win sports scholarships, students with exceptional art talent, students who belong to certain minority ethnic groups, etc. These exceptions are also quantified and added to priority scores on top of the exam scores, and are observable in our data.

[34]See Wang et al. (2021) and Li et al. (2021) for more institutional details about the CEE.

[35]Mathematics for the Humanities Track differs from that for the Science Track.

dence of admission probability alone may result in suboptimal portfolio choices (Shorrer, 2019; Rees-Jones et al., 2020). However, in our case students know their priority score and ranking by the time of application, and researchers have assumed independence in similar settings (Larroucau and Rios, 2018, 2020).

Nevertheless, to test the potential presence of pairwise correlation, we conduct an empirical test with the same specification as we used in Section 3.2 on the administrative dataset. The difference is that, in this new empirical exercise, the dependent variable is students' second choices, and the regression is run on those who were not admitted by their first choice:

$$1(\text{Admitted to Second Choices})_i = \alpha_2 + \beta_2 \hat{p}_{ij}$$

If the admission to the first choices does not correlate with the admission probability of the second choices, we would expect $\alpha_2 = 0$ and $\beta_2 = 1$, which is the null hypothesis of this exercise.

The estimation results suggest that our estimates of admission probability remain accurate conditional on the rejection of the first choices, suggesting that in our setting pairwise correlation does not significantly alter admission probability. As shown in Columns 3 and 4 of Table B2, $\hat{\alpha_2} = 0.0183$ (SE=0.0037) and -0.0002 (SE=0.0062) for the science and humanity tracks, respectively, whereas $\hat{\beta_2} = 0.9805$ (SE=0.0060) and 1.0033 (SE=0.0.0110) for the science and humanity tracks, respectively. While the null hypothesis is rejected for science track, the deviation from null is quantitatively small.

E.4 College Preferences vs. Major Preferences

Major preference does not affect assignment of college; essentially the Chinese system is a "college-then-major" system (Chen and Kesten, 2017; Calsamiglia et al., 2020). Major studies typically begin in the second year of bachelor education, and since the 2010s, the Ministry of Education (MoE) of PRC has successfully pushed for a lower barrier in major switching [36]. To assess whether major concerns affect risk taking, we asked students which factor they were most concerned about in college applications. We report the relevant statistical analysis in Table B10. In Columns 1 and 2, we regress the dummy indicating whether students consider major to be their top concern on a normalized SES index. Only 13.7% of the survey takers consider major to be their top concern, and the share is slightly lower among the advantaged students.

Consideration of major could affect students' strategy if students think ahead, and want to outcompete their peers who are admitted to the same college in terms of academic ability. To examine its quantitative impact on risk-taking, we regress the estimated unconditional probability of the first choices (Columns 3-4) and beliefs about being admitted to the first choices (Columns 5-6) on those who consider major to be of top concern. As expected, students tend to be more cautious if they consider major to be of top concern, but its quantitative impact on the probability of first choices is less than 10% compared to those who do not regard major as their top consideration. We calibrate its impact on the full

[36] The link here is an example. Since this campaign by the MoE, major distinctions have become more coarse and less of a concern to students.

sample average of first choice probabilities by calculating the product of the average impact due to major concerns and the share of students who consider major to be important. Reassuringly, it contributes at most a 1.2% increase in the mean unconditional probability of the first choices.