

Cognitive Distortions in Complex Decisions: Evidence from Centralized College Admission

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[Preliminary Draft; Latest Version [Here](#)]

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Abstract

In centralized admission systems, applicants submit a rank-order list (ROL) to indicate their preferences. The optimal decision rule is often complicated and entails an accurate understanding of backward induction and contingent reasoning. We study college admissions in Ningxia, China, to understand how students construct their lists. The admission system employs a constrained Deferred Acceptance Algorithm to match students to colleges, where each applicant can choose four colleges from hundreds of alternatives, and the priority of an applicant is determined by test scores. We find that applicants appear overly cautious with their top choices and the majority of them do not always put safer choices at a lower-ranked spot on the list. We propose a boundedly rational decision rule to explain such choices. This decision rule suggests that applicants myopically focus on the spot they are contemplating and neglect its impact on the rest of the list. We employ three strategies to differentiate our hypothesis from other explanations. First, we deploy an in-field experiment that pinpoints a core prediction of our model concerning framing effects, and observe clear support of our model. Second, we derive a set of theoretical statements about how rank-order lists change as scores rise given arbitrary preferences, construct an empirical test using exogenous variations in scores, and discover strong evidence against the rational model. Third, we conduct structural estimation that allows for flexible horizontal preferences. A mixture model with both rational and behavioral types fits the administrative data well and yields better out-of-sample predictions than the one-type rational model. 45%~55% of the sample are classified as the behavioral type, and the share is higher among the socioeconomically disadvantaged. Finally, we turn to welfare analysis, finding that the behavioral bias is responsible for 83% of the inequity in outcomes across socio-economic groups. A de-biasing intervention would substantially improve the welfare of the disadvantaged students without hurting the advantaged ones.

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 strategic sophistication on the part of the student. Constructing the optimal list is a risk-reward tradeoff problem that requires backward induction and contingent reasoning, concepts that applicants may have trouble grasping.¹ Failures to grasp the optimal strategy result 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 Algorithm³ 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 already 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 lower on the ROL. This intuition prescribes that rather than viewing each spot in isolation, the student should formulate a contingent plan to make the most of the entire portfolio by backward induction.

Is every applicant reacting optimally to this mechanism? Testing decision optimality is difficult for this type of problems in general because applicants may have heterogeneous preferences (Agarwal and Somaini, 2018, 2019). Limited progress has been made in understanding whether the

¹Chade 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) shows 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. Martínez-Marquina et al. (2019) documents how uncertainty impedes contingent reasoning.

²Impacts 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).

³As detailed in Section 2.3, this is also a serial dictatorship mechanism.

interdependency between different spots of a list, a feature that complicates decision problems in most centralized systems, could potentially generate predictable sub-optimal responses in risk taking behavior.⁴ We are able to perform this task with the help of an incentivized survey experiment, conducted right after student applicants have submitted their 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.

Further institutional features in this empirical setting make it ideally suited to analyze the decision making of students. In many settings, college admission decisions are idiosyncratic, with different schools applying different standards. However, in this setting, admission is purely determined by students' CEE scores and school-specific score cutoffs. Students know their priority scores and past cutoffs at the time of application. Admission cutoffs are stable over time, with a cross-year correlation around 0.95, implying that it is relatively easy for students to gauge admission probabilities, and that this matching market has a consensus as to which colleges are better and more selective.

How do students actually respond to the mechanism? We find that the vast majority of the students choose colleges with little risk for their fourth choices. Risk taking for their first choices, however, is highly heterogeneous, with 25% of the students choosing a safe college—i.e., one that has an unconditional acceptance probability⁵ larger than 88.5%. This suggests that many students are not sufficiently selective in their first choices. Meanwhile, 55% of the students exhibit “risk-taking reversals”, defined as ranking a less-selective college above a more-selective college on their ROLs. Under the assumption that students' preferences align with college selectivity, such reversals violate the predictions of a rational decision-making model, and have been observed elsewhere in similar mechanisms (Lucas and Mbiti, 2012; Ajayi, 2013; Rees-Jones et al., 2020; Larroucau et al., 2021). Confirming these observations, a calibrated rational model suggests that applicants are too cautious with their first choices and exhibit too many reversals in their ROLs.

These behaviors correlate with demographics and contribute to inequality in admission outcomes. As detailed in Section 4.4, students coming from disadvantaged areas, as proxied by education attainment among the 40-65 year old in students' area of residence, are substantially more cautious in their first choices and are more likely to exhibit risk-taking reversals on their ROL, further deviating from the rational benchmark. Conditional on priority scores, the most disadvantaged students on average end up in colleges whose selectivity, as measured by mean of cutoffs

⁴Some progress has been made in understanding mistakes in the absence of strategic concerns and risk-taking consideration. Artemov et al. (2017) posits that, in a strategy-proof environment, the mistakes on the lists are primarily inconsequential. Shorrer and S3v3g3 (2018) find that, in Hungary, college application dominated choices are more likely to be made when expected cost is lower and argue that multiple imperfections in decision-making may contribute to their findings. Hastings and Weinstein (2008) documents substantial presence of information frictions in school choices using randomized interventions. In a setting with strategic considerations, Rees-Jones et al. (2020) finds that decision makers neglect correlation in admission chances even in settings where correlation is of first-order concern. Kapor et al. (2020) documents 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.

⁵The unconditional probability is the probability of meeting the admission cutoff of a college.

during 2014-2018, are 0.13 standard deviation lower than the most advantaged students.

In other contexts such as taxation, health insurance, and social program take-up,⁶ agents respond to the most salient part of the problem but ignore/under-react to the others when a decision problem is complex. Anecdotal evidence from college-application advisory platforms on the Chinese Internet suggests that the most common mistake in the application process is to treat each spot as separate and identical, ignoring the interdependence between different spots. Such neglect resembles decision heuristics that have been observed when reacting to complexity in other contexts.

Motivated by previous findings as well as the literature, we introduce a boundedly rational decision rule inspired by a Directed Cognition Model (henceforth DC) (Gabaix et al., 2006) that 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. Moreover, it generates four predictions that distinguish this behavior from other possible frictions that arise in the centralized matching context.

Our first prediction, labeled **“More Cautiousness at Top”**, says that compared to the Rational Rule, the DC Rule takes substantially less risk for their first choices. However, their fourth choices are similar to their rational counterparts in terms of risk taking. This explains our previous observation that, under the rational rule, some students exhibit extreme cautiousness, and average cautiousness higher than calibrated benchmark for the first choices, but not for the fourth choices.

Our second prediction, labeled **“Risk-Taking Reversals”**, states that the DC Rule is often more likely to rank riskier colleges at a lower position in ROLs, at times generating a dominated choice in which the applicant ranks a lower-quality college higher on her list of choices. This explains the substantial presence of risk-taking reversals in our dataset.

Importantly, these two predictions are made under the assumption that students’ preferences align with the selectivity of colleges (i.e., vertical preferences). Distinguishing the DC Decision Rule from its rational counterpart when preferences are horizontal – i.e., preferences that do not completely align with competitiveness – is a vital task for our empirical analysis. To that end, we test two more predictions of our model that differentiate our hypothesis from most alternative considerations, including horizontal preferences.

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 48.7% (SE=1.8%) 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

⁶Examples in taxation include Chetty et al. (2009); Congdon et al. (2009); Abeler and Jäger (2015); Rees-Jones and Taubinsky (2020). Examples in aid application include Dynarski and Scott-Clayton (2006). Examples in health insurance include Brot-Goldberg et al. (2017). Examples in social benefits take-up include Dynarski and Scott-Clayton (2006); Bertrand et al. (2006); Bhargava and Manoli (2015).

1 SD increase in our socioeconomic status index is associated with a 7.3% (SE=1.7%) decrease in propensity to be the behavioral type.

Our fourth prediction, labeled **“Upward Movement”**, implies that if the priority score for a rational type were to increase, any listed colleges will only move down along the list. For DC decision-makers, however, any listed college would first move up along the list, and then move down, exhibiting an inverse-U shape as a function of the priority score. To empirically test the presence of upward movement, we construct small score bins, and estimate the average change of position for each listed college within each bin by exploiting small variations in rank-preserving priority scores that do not correlate with students’ preferences. This empirical exercise identifies substantial presence of the non-monotonic movements predicted by the DC model.

Finally, 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 college preferences and the DC Type by exploiting how risk-taking behavior in different positions of the list jointly respond to variation in priority scores, which causes 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 risk-taking 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. 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. The curvature over college selectivity is mild or even convex, suggesting that selective colleges are highly sought after, consistent with anecdotal evidence on the prestige of more selective colleges in China.

The DC decision rule substantially exacerbates inequality in admission outcomes. In a counterfactual scenario where all students act optimally 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 the primary factor that explains the less desirable outcomes among high-achieving disadvantaged in our context is the behavioral decision rule. An hypothetical intervention that teaches students how to correctly assess the problem⁷ will benefit the most disadvantaged quarter more than the most advantaged counterparts, by a margin of 0.07 s.d. change in test scores under the old equilibrium.

The presence of DC decision rule also has adverse impact on overall efficiencies as it decreases the welfare of both behavioral and rational applicants. The de-biasing intervention is predicted to a substantial welfare gain among behavioral applicants, which is on average larger than an increase of

⁷We conducted a small-scale pilot intervention in 2019 that taught students how to take risks. Preliminary data analysis suggests that most students are willing to take our advice. This operation was discontinued because of COVID and the associated unforeseen changes.

roughly 0.25 s.d. in the test scores under the old equilibrium. The welfare gain among the majority of rational applicants is smaller but positive due to matching efficiencies (Abdulkadiroğlu et al., 2011). 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 reach the optimality even if they recognize the strategic aspect of the mechanism, another difficulty discussed in the pioneering work by Pathak and Sönmez (2008). We show that in the presence of complexity, a specific decision heuristic can better explain participants’ strategies. The DC decision rule reflects the failure of backward induction (Camerer et al., 1993) and the tendency to make myopic choices when cognitive limitation prevents decision-makers from aggregating choices in multiple stages under uncertainty (Rabin and Weizsäcker, 2009). 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 to 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, and thus are 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 and DC Decision Rule. Section 4 presents the evidence concerning Cautiousness and Risk-Taking 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 addresses alternative hypotheses that could affect our findings. Section 9 concludes.

2 Empirical Setting

2.1 Summary of Events Before Admission Process

Figure 1 presents the timeline of the admission procedure in 2020 (the first timeline) as well as before 2020 (the second timeline). The postponement in 2020 happened because of COVID-19, and as a result all the related activities were postponed by exactly one month. Therefore, the order of and duration between admission procedures was unchanged to minimize the impact of the pandemic on student applicants and college admission committees.

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 admission. As elaborated in Section 2.2, the exam performance determines students' priority scores in the admission system and thus has a predominant impact on students' application strategies.

The admission process (and therefore ROL) 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).

When students are notified of their test scores and corresponding provincial rankings, the 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. The share of students who are eligible for elite colleges is roughly 20 ~ 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.

The application process is time constrained and cognitively demanding. The time to contemplate college choices is less than three weeks if a student starts to think about it right after taking the CEE, and is less than one week if effective decision-making starts after the notification of CEE scores. Applicants must submit their ROLs before the deadline. In addition to the time constraint, students have no chance 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 ROL is processed⁸. This type of mistake concurs with the DC decision rule that we propose in this paper.

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

2.2 Priority Score

The priority score is almost completely determined by the College Entrance Exam (CEE)⁹. 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. As demonstrated in Figure 1, 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, Mathematics¹⁰ 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.

2.3 Rules of Admission

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 quota. 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.

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. Therefore 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 have 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

⁹Exceptions 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 datasets.

¹⁰Mathematics for the Humanities Track differs from that for the Science Track.

using the same priority score and similar algorithms ¹¹.

We can tell from the rules above that the structure of preferences on the college side is unusually simple compared to other matching markets where there is no obvious priority score (e.g., NRMP (Roth and Peranson, 1999)), or where different priority scores are adopted in different schools (e.g., New Haven School Matching (Kapor et al., 2020)). The one-dimensional priority score enables us to interpret this specific matching market in canonical contexts. Mapping this context onto bidding, for example, students, being aware of their “WTP” (priority score), can submit up to four bids to colleges, whose “prices” (admission cutoffs) are unknown by the time of “bid submission” (ROL submission).

2.4 Data

We use two sources of data. The first is the administrative dataset generated by the centralized admission system that records the application behavior of students from 2014 to 2018. The dataset is maintained by the Ningxia Provincial Education Authorities. The second is an online survey that we set up in 2020 that targets the same type of students we analyze in the administrative dataset (i.e., CEE takers in Ningxia applying to first-tier colleges).

(I) Administrative Data With the help of the Ningxia Education Authority, we obtained access to administrative data from 2014 to 2018, covering 6,000-9,000 first-tier eligible science track students in each admission cycle. The number is considerably lower for humanities track students, amounting to roughly 1,500-2,000. The data contains students’ CEE scores, ROLs, admission outcomes, and some demographic information, such as the county, city and street of their residence address (available only in 2015, 2017, 2018), gender, age, ethnicity, parents’ occupation, rural/urban status, and schools where they received elementary and secondary education.

(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 1, the survey was conducted right after students submitted their ROL for first-tier colleges, but before they were notified of the admission outcomes¹². 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

¹¹Students can rank four 2nd-tier colleges and four 3rd-tier colleges

¹²We 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. Third, we could not wait very long after students had submitted their applications, because imperfect recall or self-rationalization upon receipt of admission outcomes might impede accurate measurement of their beliefs and preferences.

of application advice, and preferences over college characteristics. The second part elicited their beliefs about unconditional admission probability¹³ of the colleges on their ROL (0% ~ 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.

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 game¹⁴, 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, as 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 to the n colleges that she is contemplating. Denote the unconditional assignment probabilities (i.e., probability of meeting the cutoff) of the n colleges by p_1, p_2, \dots, p_n respectively. For the purpose of presentation and without loss of generality, assume that $p_1 < p_2 < \dots < p_n$ (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, \dots, 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 probabilities p_j , for which we need to construct measures to approximate what

¹³The 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.

¹⁴This treatment is conventional in this literature. Examples include Agarwal and Somaini (2018); Kapor et al. (2020); Calsamiglia et al. (2020).

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 cycle¹⁵.

The cutoffs in past years can reliably predict the current cutoffs. In Figure 2, 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 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 competitiveness of a college overall 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 A1a, 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 2 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 :

$$\hat{\sigma}_j \equiv \hat{\beta}_0 + \sum_{k=1}^4 \hat{\beta}_k \mu_j^k$$

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

$$\hat{p}_{ij} \equiv \Phi\left(\frac{s_i - \mu_j}{\hat{\sigma}_j}\right)$$

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

We follow [Kapor et al. \(2020\)](#) to validate the estimates of admission probabilities. Specifically,

¹⁵See [here](#) for a well-known website that documents past admission cutoffs.

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 estimation results suggest that our estimates accurately reflect the actual unconditional admission probability. As shown in Columns (1) and (2) of Table B2, $\hat{\alpha}_1 = -0.0043$ (SE=0.0024) and -0.0050 (SE=0.0040) for the science and humanity tracks, respectively, and $\hat{\beta}_1 = 1.0015$ (SE=0.0043) and 1.0117 (SE=0.0081) for science and humanity tracks, respectively. The p-values of the F-tests are 0.074 and 0.328, respectively, meaning that we fail to reject the null hypothesis.

To double-check that our estimates capture the observation that the uncertainty of cutoffs is larger for colleges of medium competitiveness, in Figure A1b 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 takeaway from the graph is that our estimates do reflect the heterogeneity of volatility in admission cutoffs for colleges with different degrees of competitiveness, and that the normal distribution of different variances, as proposed above, 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 $(1 - p_{j_1})p_{j_2}$ ¹⁶. 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. Therefore, her expected utility from the portfolio $\{j_1, j_2, j_3, j_4\}$ is:

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

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 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

¹⁶Here we are assuming that admission probability is independent because we believe that this is a reasonable approximation in our empirical setting. See Section 8.2 for a detailed discussion of why the assumption about independence is justified.

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 number¹⁷, a computationally difficult task.

Chade and Smith (2006) proposes a computationally simple method that solves for this portfolio choice problem. Let dummy χ_j denote the event that a student's priority score meets the admission cutoff of college j . The utility of portfolio $\{j_1, j_2, j_3, j_4\}$ is defined as

$$PF(\{j_1, j_2, j_3, j_4\}) \equiv \max\{\chi_{j_1}u_{j_1}, \chi_{j_2}u_{j_2}, \chi_{j_3}u_{j_3}, \chi_{j_4}u_{j_4}, \underline{u}\}$$

$E[PF(\{j_1, j_2, j_3, j_4\})] = EU(\{j_1, j_2, j_3, j_4\})$ when colleges are correctly ordered in the list according to their utilities. Hence a correct way to construct the portfolio consists of the five steps below:

- **Step 1:** Choose college a such that $PF(\{a\})$ is maximized.
- **Step 2:** Given a , choose college b such that $PF(\{a, b\})$ is maximized.
- **Step 3:** Given a, b , choose college c such that $PF(\{a, b, c\})$ is maximized.
- **Step 4:** Given a, b, c , choose college d such that $PF(\{a, b, c, d\})$ is maximized.
- **Step 5:** Order a, b, c, d such that the one with higher utilities is always ranked higher.

What are the implications of such procedures? Suppose the right answer for Mei's best ROL is $[a^*, b^*, c^*, d^*]$. 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. This happens because the optimal amount of risk to take is different across positions. As a necessary condition, 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 matters 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 j_4 \rightarrow (outside option)
- (blank) \rightarrow (blank) \rightarrow j_3 \rightarrow j_4 \rightarrow (outside option)
- (blank) \rightarrow j_2 \rightarrow j_3 \rightarrow j_4 \rightarrow (outside option)
- j_1 \rightarrow j_2 \rightarrow j_3 \rightarrow j_4 \rightarrow (outside option)

¹⁷To be precise, the number is $\binom{n}{4}$, which amounts to 4 billion in our context.

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. The five-step decision making is correct regardless of preference structure, but the mapping between choices in each step and its position on the list becomes more complicated than backward induction.

3.4 Formulation of DC Decision Rule

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 also 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) (henceforth, DC). 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 maximize

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

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, as Hua proceeds in a natural order by considering the first choices before the rest of the ROL. Second, as 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 4.3, and discuss the heterogeneity of in risk-taking behavior across students of differential SES status in Section 4.4. Note that as a first step, throughout this entire section we are assuming that students' preference is vertical or deviating from vertical in some simple parametric way. The purpose of such discussion is to illustrate the impact of the DC Model in the most straightforward way.

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 high. Figure A2a 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%. We therefore focus on the top 60% in this and subsequent sections.

4.1 Predictions: Cautiousness and Reversal under Vertical Preferences

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 step q . 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 before the q th step of decision making, including the outside option. Define the propensity to take risk as a function of step number (i.e. q) 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 .

Prediction 1 (Cautiousness at Top) *For any step $q > 1$, the Rational Rule takes more risks in listing their first choice than the DC Rule. Moreover, the gap between risk taking between the Rational and the DC Type is increasing in q .*

This prediction holds because Mei can correctly calculate the expected value as $\underline{u} = PF_1 < PF_2 < PF_3 < PF_4$, whereas Hua ignores the rest of the portfolio and make decisions as if $PF_1 = PF_2 = PF_3 = PF_4 = \underline{u}$. Mei's cautiousness is as great as Hua's in the first step. As $U_a - U_b$ is increasing in the expected utility of backup list, Mei is more inclined than Hua to take a risk in later steps. Intuitively, as the first choice is usually made in the last step due to the logic of backward induction, the risk-taking gap between the DC Rule and the Rational Rule will be maximal for the first choices.

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 (Risk-Taking 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 at higher-ranked position, and the logic of backward induction illustrates why such portfolio choices are optimal. 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 Figure 3a presents the mean and 75th percentile of unconditional admission probability that we construct as described in Section 3.2, for each choice on the lists. The median of the probability, as indicated by the white dashed line, is 48.4%, 69.6%, 81.1%, 90.6%, 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 risk in their first and second choices, as the 75th percentile of probability is 88.5% and 98.6% respectively. On the other hand, the heterogeneity of probability is minimal for the fourth choices, where the 25th percentile is 95.4%, suggesting that the vast majority of students are taking little risk for their bottom choices, which makes sense in a high-stakes environment. However, summary statistics in probability alone are insufficient, as we need to calibrate students' choices to map the level of probability to familiar measures in risk preferences.

Share of “Risk-Taking 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 risk-taking reversals on the ROLs. We plot the results in Figure 3b, and find that more than 55.8% of the ROLs exhibit risk-taking reversals ($R > 0\%$). Further limiting our scope to the case of “serious” reversals, where an ROL is counted only when R exceed a certain positive threshold ($R\% > 25\%, R\% > 50\%, R\% > 75\%$), the share mechanically decreases but still remains non-negligible. For example, the share is 24.6% 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 “risk-taking reversals” on their lists. This clearly rejects the joint hypothesis that students have perfect vertical preferences and are following the rational benchmark.

4.3 Calibrating Rational Benchmark

To quantify whether findings in Section 4.2 could be rationalized by risk preferences (curvature over competitiveness) that alter students’ intensity of vertical preferences, or random idiosyncratic shocks to students’ preferences as a proxy for horizontal preferences, we calibrate a very simple model where the utility of college j for student i is:

$$u_{ij} = \frac{(c_j - m)^{1-\rho} - 1}{1 - \rho} + \epsilon_{ij}$$

where c_j is the normalized competitiveness of college j as measured by average cutoffs during 2014-2018. $m \equiv \min_x \{c_x\}$ is the lowest value of the college in this measure, so that $(c_j - m)$ is guaranteed to be positive, with the standard deviation being 1. ρ represents the curvature of preferences over the competitiveness of a college. $\epsilon_{ij} \sim N(0, \sigma^2)$ is the idiosyncratic preference shock over colleges. This simple model captures the core components of preferences: vertical preferences, as controlled by the curvature ρ , and idiosyncratic horizontal preferences, controlled by the level of σ . Lower ρ and σ imply that a larger share of variation in preferences is explained by vertical preferences.

We focus on three specific statistics for the calibration: correlation of cutoffs in 2017 and 2018, mean probability of first choices, and the share of reversals. In this model, reversals can only be rationalized by introducing horizontal preferences, i.e., increasing σ . A larger idiosyncratic shock, however, also decreases the stability of cutoffs because competitiveness contributes to a smaller share of utility in that case. As shown in Figures 4b and 4c, creating a substantial share of reversal

necessitates significantly lower correlation in cutoffs. In other words, the stability of cutoffs bounds the level of idiosyncratic shock allowed in the specification.

Moreover, as shown in Figure 4a, the curvature that rationalizes the cautiousness for the first choices is quantitatively implausible and needs additional restrictions in horizontal preferences. When competitive colleges are highly sought after, as in our context, the utility differences between the top college and the median, Δu_{tm} , should be no smaller than the utility difference between the median and the bottom, Δu_{mb} . In this case, while the mean of probability from the data is 49.7%, the simulated mean when $\Delta u_{tm} \geq \Delta u_{mb}$ ranges from 22.2% to 31.4% regardless of the level of idiosyncratic shock, roughly 20% less than what the data reveals. The level of cautiousness in data is achieved only when students are almost indifferent between a median and a bottom college ($\Delta u_{tm} < 10^{-7} \Delta u_{mb}$), under the assumption that there are no horizontal preferences at all. When just a little idiosyncratic taste heterogeneity is introduced, the cautiousness wanes and the simulated mean of probability drops to less than 45% no matter how small Δu_{tm} is.

Certainly, this model does not address many important forms of horizontal preferences. The rejection indicates that either more complicated horizontal preferences or alternative behavioral considerations are needed to explain these three empirical patterns at the same time.

4.4 Socioeconomically Disadvantaged

Depart Further From Calibrated Benchmark

A large literature documents that socioeconomically disadvantaged students are particularly bad at strategizing in centralized systems (Lucas and Mbiti, 2012; Ajayi, 2013; De Haan et al., 2015; Shorrer and S3v3g3g, 2018; Kapor et al., 2020). To examine whether demographics are important in our context, we choose average educational attainment at township level¹⁸ to approximate socioeconomic status¹⁹. As we also have access to students' home addresses in 2015, 2017, and 2018, 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. 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). In the following exercise, we split students into four groups according to their SES, and focus our attention on the most advantaged quartile ($\text{edu} > 9.88$ years) and the most disadvantaged quartile ($\text{edu} < 7.80$ years). Importantly, as 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 applicants' preferences over physical distance.

In Figure 5a, we compute the statistics in Section 4.2 for the most advantaged and the most disadvantaged quartile, respectively. All the statistics have been reweighted to take into account any differences in priority score, so the patterns cannot be explained by students facing different

¹⁸Roughly speaking, township is equivalent to zip code in the US.

¹⁹We obtain statistics on average years of education among adults between 40-65 at township level from the China Census in 2010.

choice sets due to differential priority scores.

The mean probability of the first choices among the socioeconomically disadvantaged students (53.8%) is less than their advantaged counterparts (45.7%), after priority scores have been controlled by reweighting. However, for their fourth choices, the probability among the disadvantaged (91.3%) is slightly less than their advantaged counterparts (92.9%)²⁰.

Do the differences hold statistically? We use the following specification to quantify the difference:

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

Where *Disadv* indicates whether students are from a lower SES group, $f(\text{Priority Score})$ and $g(\text{Priority Score})$ represents a fourth-order polynomial of priority score²¹. 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, the results confirm our visual perception regarding the first and fourth choices. After introducing the full set of controls as listed in Panel C, the mean probability of the first choices among the disadvantaged is 6.74% (SE 0.40%) more than their advantaged counterparts (Column 1), and the mean probability of the fourth choices among the disadvantaged is 2.24% (SE 0.40%) less than their advantaged counterparts (Column 2). As a result, the gap between the advantaged and the disadvantaged with regard to fourth-first choice probability differences amounts to 8.98% (SE 0.78%). Panel B demonstrates that the signs of the Adv-Disadv gaps remain the same as the main effect in corresponding columns over the whole range of priority scores, though the effect is insignificant among those with the highest priority scores.

Figure 5b plots the share of reversals for the most advantaged and disadvantaged quartiles, respectively. After differences in priority scores have been adjusted, 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 19.7%, and the weighted share of reversals among the disadvantaged is 26.1%, roughly 40% higher than the advantaged.

In Table 2 we consider the following regression:

$$1(R > X\%) = \text{Disadv} + f(\text{Priority Score}) + \text{Disadv} * g(\text{Priority Score}) + \text{other controls} \quad (4)$$

where we vary the threshold X so that it equals 0, 25, 50, or 75% in Columns 1, 2, 3, and

²⁰Please refer to Figure A2b for a complete breakdown of admission probability by priority score, across students in the most advantaged and most disadvantaged quartiles.

²¹Each 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.

4, respectively. As reported in Panel A, the qualitative results, after priority score has been fully controlled for, are consistent with the graphical observation, with the gap in the share of reversal remaining at about 5%. As shown in Column (2), for example, after controls listed in Panel C are included, the estimated share of reversal (threshold $R > 25\%$) is 6.64% (SE 0.80%) higher among the most disadvantaged. As presented in Panel B, the gap between the disadvantaged and their counterparts persists at different levels of priority score, though sometimes insignificantly so among those with the highest priority scores.

We also restrict our simulation exercise in Section 4.3 to the most disadvantaged quartile. Figure A5 presents the main results. The takeaway is that the disadvantaged are more cautious in their first choices (unadjusted mean: 50.9%) and exhibit even more risk-taking reversals (unadjusted mean: 28.0%), such that the simple utility model has a harder time rationalizing their choice patterns. For example, the share of reversals among the disadvantaged never exceeds 23.9% even with substantial idiosyncratic shock ($\sigma = 1$) and ($\Delta u_{tm} \approx 0$).

To examine whether pursuing different strategies systematically affects admission outcomes among the disadvantaged, we run the following two groups of regressions:

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

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 suggest that socioeconomically disadvantaged students on average end up in less selective colleges compared to their advantaged counterparts, even after other demographic variables that are correlated with socioeconomic status have been included. In one of our specifications, 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 Support for Directed Cognition: Testing Framing Effect

The predictions concerning cautiousness and risk-taking reversals in Section 4.1 differentiate the DC Rule from the Rational Rule under the assumption of perfect vertical preferences, which is unlikely to hold in case of real college preferences. To tackle this issue, we design a survey experiment in which students make college and lottery choices where 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. We mathematically introduce the prediction itself Section 5.1, discuss the details about the survey experiment in Section 5.2, and present the data analysis in Section 5.3.

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 r th 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 r th 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 present in the form of lottery can “de-biased” by bringing the utility of backup choices to their 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 r th 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, a DC Type will be more risk-taking in the lottery questions.*

5.2 Details of Survey Questions

The first and third group of questions asked students to take the amount of risks they prefer in each hypothetical situation. They need to choose one from College X or College Y, whose payoffs in the event of admission and unconditional admission probability have been specified in Panels A2 and C2 of Table B4 respectively, and fill in the first spot of the ROL. For each MPL, 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, 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 the state when rejection of the first choice occurs is 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.

How do responses to these survey questions map onto attitudes of risk taking? 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. Because Y is the riskier option, the earlier the switching points, the more risk-taking the students.

We took several measures to minimize misunderstanding and maximize the efficacy of survey responses. First, students were directed to correctly read through our explanations about the questions and complete comprehension checks before answering these questions. Second, the college names in the table were customized according to survey takers' CEE score: both College X and Y on their screen were real Chinese colleges that are within their reach, with Y being more competitive; backup spots are filled with local colleges, which are generally considered to be worse given the under-developed status of Ningxia. Third, to minimize the possibility of personal preferences interfering with choices in ROL questions, we framed the questions as students themselves making choices for their hypothetical friends who share their risk preferences.

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 plotting the joint distribution of students' responses to Question Groups 1 and 2 in Figure 6. About 43% of the data points are located around the diagonal line (blue blocks), which represent students who take similar levels of risk across these two questions, i.e., exhibit consistent risk preferences across equivalent questions that are merely framed differently. This is consistent with the rational decision rule. Meanwhile, 51.9% of data points are located at the top right (red blocks), indicating that some students are taking substantially less risk in the ROL question compared to its lottery equivalent, consistent with the DC decision rule.

Are there more DC Type students among disadvantaged students? This is suggested by Section

4.4, where socioeconomically disadvantaged students depart farther from the prediction of the rational benchmark. In order to answer this question, we need to quantify the extent of inconsistency. The two groups of questions enable us to identify the “indifference point” for the upside payment above which the riskier option is more desirable. Let R denote the amount such that the student is indifferent between College X (25 CNY, 50%) and College Y (R CNY, 25 %) and between Lottery X (25 CNY, 50%; 20 CNY, 50%) and Lottery Y (R CNY, 25%; 20 CNY, 75%). We run the following regression to test whether disadvantaged groups, on average, answer these two groups of questions more inconsistently:

$$|R - Y| = \beta \text{SES Index} + \text{Controls}$$

where SES Index is parents’ average years of education, as elicited from the data. We report the results in Table 3, Panel A. Consistent with Figure 6, the inconsistency of response across the two groups of questions is substantial, with the mean of the inconsistency measure being 11.618. Moreover, the inconsistency is more pronounced among the socioeconomically disadvantaged students, and the relationship is robust across different specifications. With all available controls included, a 1 SD increase in SES Index is associated with a 1.337 (SE=0.360) decrease in the inconsistency measure.

To estimate the share of the DC Type in the survey sample, we model survey takers’ risk-taking behavior by assuming that students have constant relative risk aversion (CRRA) preferences:

$$u = \frac{(c + B)^{1-\rho} - 1}{1 - \rho}$$

where B is background consumption, which we set to be 10 CNY²². We allow ρ to vary on Edu, parents’ average years of education, and CEE, the quantile of Priority Score:

$$\rho = \alpha_0 + \alpha_1 \text{SES} + \alpha_2 \text{Score} + \epsilon_\rho$$

where $\epsilon_\rho \sim N(0, \sigma_\rho^2)$. Following [Von Gaudecker et al. \(2011\)](#), we model the noise in decision making in terms of its impact on perceived certainty equivalents of a risky choice. Decision noise $\epsilon \sim N(0, \sigma^2)$ is independent across different questions and will govern the choice: for example, if an individual prefers College $X \equiv (25, 50\%; 20, 50\%)$ to $Y(m) \equiv (m, 25\%; 20, 75\%)$ when $m = 30$, but switches to $Y(m)$ when $m \geq 35$, this means that:

$$CE(X, \rho) + \epsilon \geq CE(Y(30, \rho))$$

and

$$CE(X, \rho) + \epsilon < CE(Y(35, \rho))$$

where $CE(L, \rho)$ is the certainty equivalent of lottery L when the CRRA coefficient is ρ .

²²Roughly the value of one meal in China.

Regardless of type, students with the same ρ in our model will produce the same distribution of choices in the standard lottery question (Question Group 2). However, in Question Groups 1 and 3, different types of individuals behave differently despite having the same risk preferences. Denote the lottery presentation of college X and Y from Question Groups 1 and 3 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. While the rational type will correctly translate the ROL question to its lottery representation, a DC Type processes the ROL questions differently:

$$CE_{\text{DC Type}}(X(b)) = CE(X(0))$$

and

$$CE_{\text{DC Type}}(Y(m, b)) = CE(Y(m, 0))$$

Thus, a DC Type distorts the downside of the lottery to a lower level, and appears to be more cautious.

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). To put it into our context, the sincere type predicts that, in the ROL presentation, students will always prefer colleges with the highest payoffs, ignoring the probability of admission. In terms of certainty equivalents:

$$CE_{\text{Sincere Type}}(X(b)) = 25$$

and

$$CE_{\text{Sincere Type}}(Y(m, b)) = m$$

While we do not find much evidence supporting the presence of this type in administrative data, as very few students consistently choose overly competitive colleges throughout the whole ROL, this type can be well identified in our survey.

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 = -5770.302, 9 parameters) compared to a model in Column 1 that only allows for the rational type (Log Likelihood = -6271.152, 6 parameters). The improvement is substantial, such that the Bayesian Information Criterion also favors the mixture model (BIC metrics = 11605.88) over the single-type rational model (BIC metrics = 12585.82). The impact of including the sincere type (Column 3), while it also improves the fit, is limited compared to the DC Type (Log Likelihood = -5733.326, 10 parameters). Consistent with this observation, the estimated share of the DC Type is 48.7%

in our preferred specification, whereas the share of the sincere type is about 3% (Column 3). The marginal effect of socioeconomic status is also statistically significant, where a 1 SD increase in the SES Index is associated with a 7.3% (SE=1.7%) decrease in the share of the DC Type. Lastly, heterogeneity of risk preferences plays little role in fitting the data, and overall the risk aversion among the survey takers is moderate (mean of CRRA coefficient 0.079, SE=0.013).

6 Support for Directed Cognition: Testing Upward Movement

While Section 5 shows that a substantial portion of students in the survey experiment adopts the DC Model, and the evidence is not susceptible to horizontal or heterogeneous preferences, we do not know whether administrative data, the full sample of college applicants, could differentiate the DC Rule from the Rational Rule when the assumption about vertical preferences is relaxed. The difficulty of this exercise is that reversals or cautiousness on their own is insufficient.

To detect the DC Type, in this section we rely on a variation in priority score that is orthogonal to preferences. As discussed in Section 6.1, under some assumption about the conditional homogeneity of preferences across students, we would be able to differentiate the DC students' behavior from their rational counterparts by looking at their responses to this variation. The existence of such variation is discussed in Section 6.2. The empirical analysis is presented in Section 6.3.

6.1 Prediction: Position Movement in ROL

This subsection presents another prediction that tells apart 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 under 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 7a 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 subsequent empirical exercise in Section 6.

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:

²³Probability of meeting the cutoff of A .

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

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 characterize \mathcal{R} :

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 $\mathcal{C}_{(u, A, \kappa)}^{RN} = \{s | \mathcal{R}(u, A, s) = \kappa\}$ is connected.*

The key assumptions, as detailed in Appendix D, says that increases in priority score will make the assignment probability of the safer college increases at a lower rate than the riskier one. As discussed in Appendix D, this statement is true for any pair of colleges whose cutoff distribution is log-concave²⁴ 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 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, it first appears at the fourth choice once its probability is just high enough to exceed the previously 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), it may move **up** as s increases, because p_A affects how A is ranked under the DC rule. It starts to move down gradually if s is so high that other better colleges are within the reach. Figure 7b 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 7a, it becomes apparent that the “climbing up to the top” movement to the left of the peak in Figure 7b distinguishes DC from the rational rule. The following theorem mathematically characterizes \mathcal{D} , when Assumption 1, 2, 3, as detailed in Appendix D, hold:

Theorem 2 *Under Assumption 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 $\mathcal{D}(u, A, s) = \xi$.*

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 randomly if

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

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

more than two colleges tie, similar results emerge as well. 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 rational decision rule, but may move upward under the DC decision rule.*

6.2 Variations in priority score that are orthogonal to preferences

As students cannot perfectly control exam performance, conceptually, there will be random variation of priority scores among students with the same academic ability. This conceptual variation is hard to quantify, but anecdotal evidence suggests that it is typical to have a CEE score 30-35 points away from performance in mock exams.²⁶

More importantly, even 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 A7a. 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 score²⁷ on the polynomials of percentiles of each subject:

$$\text{Rank-Preserving Score}_i = f(\text{Chinese}\%_i, \text{Math}\%_i, \text{English}\%_i, \text{Comprehensive}\%_i) + \nu_i \quad (5)$$

If the regression is run within each year, the score should be perfectly predicted by the quantiles, which we confirm. 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 A7b. 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.

²⁶We obtained access to the scores in mock exams as well as the CEE in a high school of another province. Regression analysis suggest that the standard deviation of the mock exam-CEE score gap is roughly 32 points. Also, see [here](#) (in Chinese) for discussion regarding volatility of performance in the CEE. The online platform in the link is the Chinese counterpart of Quora.

²⁷Converting raw CEE score to its 2018 rank-preserving equivalent, as in Section 2.

6.3 Testing Upward Movement in ROL: Data Analysis

For each student i and its selected college j , we divide the students according to its predicted probabilities in the absence of the score shock $\hat{\nu}_i$ (i.e. the probabilities converted from the predicted ability \hat{f}_i) into ten groups: 0.1% ~ 10%, 10% ~ 20%, 20% ~ 30%, ... 80% ~ 90%, 90% ~ 99.9% and generate ten dummies. This set of variables is aimed to capture any heterogeneity in preferences that associate with students academic ability. In other words, within each probability bin, students have essentially the same academic ability and thus change in preferences that are associated with academic ability has been controlled. Armed with the shock $\hat{\nu}_i$, we run the following random-coefficient regression to test our hypothesis:

$$y_{ij} = \beta_{(j,SES\ Quarter,Prob\ Bin)} \hat{f}_i + \gamma_{(j,SES\ Quarter,Prob\ Bin)} \hat{\nu}_i + FE_j * FE_{SES\ Quarter} * FE_{Prob\ Bin} + \epsilon_{ij} \quad (6)$$

where y_{ij} is the position of college j on student i 's list (i.e. the vertical axis of Figure 7a and Figure 7b), FE_j is the college fixed effects that aim to capture average preferences over college j non-parametrically. $FE_{SES\ Quarter}$ is dummy for which socio-economic status quarter 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 7a and Figure 7b) in within 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 movement²⁸. In other words, students who have similar socio-economic status, academic ability, and choose to include the same college in their list (regardless of the position of the college) are assumed to have homogeneous preferences over relevant colleges.

Table 4 reports the estimated mean μ_γ and standard deviation σ_γ of $\hat{\gamma}_{(j,SES)}$ in Column 2 and 3 respectively. The mean of $\hat{\gamma}_{(j,SES)}$ is positive when predicted admission probability of student i admitted by college j in the absence of the score shock is lower than 20%, suggesting substantial presence of the upward movement. When the predicted admission probability is above 20%, the estimated mean is around zero or negative, which does not necessarily indicate lack of DC Type. Figure 7c illustrate this point by plotting the estimated mean and its confidence interval in Table 4. As the movement among the DC Type is predicted to be initially upward when the probability is lower, and become downward when the probability is higher (Figure 7b), the initial positiveness and subsequent decline in the mean from Figure 7c could be interpreted as evidence supporting the presence of the DC Type. Moreover, the heterogeneity in $\hat{\gamma}_{(j,SES)}$ across college*SES cluster is not negligible when the predicted admission probability is above 20%, which also points to the massive presence of upward movement for higher probability bins.

²⁸ 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

As discussed in previous sections, risk taking behavior can be used to infer the presence of the DC Type in the following scenario: (I) using administrative data and maintaining assumptions about vertical preferences (Section 4); (II) allowing for extra data collection in a carefully controlled decision environment (Section 5); (III) using administrative data and assuming conditional homogeneous (but not vertical) preferences within each subgroup as determined by observables (Section 6). The aim of this section, structural estimation, is to quantify the *share* of DC students using administrative data alone when certain *heterogeneous* preferences are taken into account. Further, the estimation results will be used to conduct counterfactual analysis.

As 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 harder to understand how structural model can identify the DC Type. We discuss the intuition of identification in Section 7.1 in a simple setting with heterogeneous and horizontal preferences. We implement a parametrized structural model to jointly estimate the share of the DC Type and preferences (Section 7.2, 7.3), and use the estimation results (Section 7.4) to discuss the welfare implication of de-biasing and alternative mechanisms (Section 7.5).

7.1 Prediction of the DC Rule & Intuition of Identification

As discussed in Section 4, in terms of risk taking behavior, cautiousness at the top spots (compared to the bottom spots) and risk-taking reversals are indicative of the DC Rule. Without additional variations, however, seemingly sub-optimal risk-taking behavior is also compatible with heterogeneous and horizontal preferences, which our structural model will take into account.

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 probability as a result is arguably orthogonal to preferences. In addition, we are assuming in this section that students with close priority scores share the same distribution of preferences.

How does this variation contribute to identification? Higher priority score increases the assignment probability of all colleges, *at different rate*. 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.

Setting There are four colleges, A_1 , A_2 , B_1 , B_2 . Let s denote priority score. A_1 and A_2 are risky (but potentially more desirable) colleges, and both of them has unconditional assignment probability $p_A(s)$, and admission utility $\delta > 0$. B_1 and B_2 are safe colleges, and both of them has unconditional assignment probability $p_B(s) > p_A(s)$, and admission utility is 2 and 1 respectively. All the probabilities are independent. Students need to select two colleges from the four under

constrained Deferred Acceptance Algorithm. Utility of 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

$$\frac{p_A(s)}{p_B(s)} > \frac{2}{\delta} \quad (7)$$

As shown in Figure A6, 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 probability are increasing at different rate²⁹. If we can observe an individual making choices given 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 $B1$. For a group of students, the rate at which students switching from $A1$ to $B1$ consequently identifies the density of δ .

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

Theorem 3 (Anomalous List Switch) *When $\frac{p_A(s)}{p_B(s)} < \frac{1}{2}$, only the DC Type switches from “cautious” to “reversal”. When $\frac{1}{2} < \frac{p_A(s)}{p_B(s)} < 1$, only the DC Type switches from “reversal” to “reckless”.*

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 $A2$, which is δ , is high. For the Rational Type, high δ rules out the possibility of a reversal. Moreover, the point at which switch happens also reveals preference intensity of the DC Type. The rate at which list switch happens hence identifies the probability density of δ .

This illustrates that in the presence of variation in s , the presence of risk-taking reversals can be quite revealing. In the estimation, we assume that students whose scores belong to the same

²⁹As 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 similar standard deviation. When the dispersion is different, the range of the ratio will be usually wider, though not necessarily increasing in s .

quintile share the same distribution of preferences, and use the mean of assignment probability for the four choices, as well as the distribution of assignment probability gap in each pair of reversals to capture the extent of risk-taking reversals.

7.2 Setup

Structure of College Preferences We allow for substantial, flexible preference heterogeneity in our estimation. For individual i , the utility of admission to college j is

$$u_{ij} = f(\theta_i^C, C_{ij}, SES_i) + g(\theta_i^d, d_j, SES_i) + h(\theta_i^X, X_j, SES_i) + O_i + \epsilon_{ij} \quad (8)$$

where C_{ij} is the competitiveness of college j with respect to student i , SES_i is the average educational attainment in student i 's township of residence. As detailed in Appendix C, function $f(\cdot)$ controls the curvature over college preferences and takes the form of the CRRA function, with the curvature parameter being θ_i^C ³⁰. 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 $g(\cdot)$ controls preferences for distance and is quadratic with parameter vector θ_i^d . θ_i^d is jointly normally distributed with 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.

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 :

$$P(\text{DC Type} | \text{SES}_i) = \frac{\exp(\gamma_0 + \gamma_1 * \text{SES}_i)}{1 + \exp(\gamma_0 + \gamma_1 * \text{SES}_i)} \quad (9)$$

Admission Probability In the benchmark estimation, we use the estimated probability \hat{p}_{ij} as in Section 3.2.

³⁰As in Section 4.3, we ensure that C_{ij} is positive by taking the difference between itself and the minimally competitive college.

7.3 Estimation Strategy and Identification

Following Section 4, we focus on students whose priority score percentile is above 40% because the identification of departure from the optimal benchmark comes from the coexistence of reversals and cautiousness. As discussed in Section 4.2, these are more pronounced among students whose priority score is high enough such that college choices become less binding. We split our sample according to students' CEE score and conduct the estimation for 40% ~ 60%, 60% ~ 80%, 80% ~ 100% separately because those of different levels of academic ability tend to choose colleges of different levels of competitiveness, as demonstrated in Figure A8. Thus, to minimize the impact of unobserved preference heterogeneity it is better to estimate among students of similar level of priority scores.

We include moments such as the mean assignment probability of the first, second, third, fourth choices, as well as the share of reversals to target the moments that are directly related to the predictions of the DC Model³¹. In this parametrized model, the moments on characteristics of the listed colleges (physical distance, as well as share of 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 assignment probability of a single choice. Other horizontal preferences are assumed to be idiosyncratic, and thus bounded by competitiveness (i.e., cutoffs) of the choice. Estimated values of the moments for students whose score belongs to 40 ~ 60, 60 ~ 80, 80 ~ 100 percentile are reported in Table B9, B12, B15 respectively³².

Based on the discussion about upward movements in Section 6.1, all the moments are constructed for the first, second, third and fourth choices separately. Moreover, informed by our findings in Section 4.4, 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 Simulated Method of Moments to estimate this model. We simulate each students' choices 50 times, and calculate the simulated moments by averaging across different rounds of simulation for all students in each SES*Score cell. 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 the estimated variance being:

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

³¹Maximum likelihood estimation using ROLs, as in Agarwal and Somaini (2018); Calsamiglia et al. (2020); Kapor et al. (2020) is relatively more difficult as 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).

³²We also report the moment for 0 ~ 20 and 20 ~ 40 percentile in Table B24, B25

where 50 corresponds to the number of simulated choices for each observation (Laibson et al., 2007; DellaVigna et al., 2016), $\hat{G} \equiv \frac{\partial m(\hat{\theta})'}{\partial \hat{\theta}}$ 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.

7.4 Estimation Results

Table 5 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 and MMSC-BIC metric³³ (Andrews and Lu, 2001), an analogue of Bayesian Information Criterion, favors the mixture model over 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 propensity of being a DC Type. This negative effect is less than the estimated effect from the survey (7.3%, SE=1.7%), though the estimates are not statistically different.

The estimated curvature over competitiveness is mild and sometimes positive, ranging from -0.486 to 0.413 (ρ in CRRA specification), with all standard errors below 0.1. A general pattern is that, when only the rational type is allowed, the estimated curvature is larger than when both types are present. This suggests that the model does try to rationalize the cautiousness by increasing curvature. However, even in this case the curvature is mild ($\rho < 0.5$), which suggests that increasing curvature does not further improve fit despite its ability to generate cautiousness, because an extremely curved utility function will generate implausible choice patterns over other observables. For the mixture model, the curvature is in the negative territory, suggesting that top colleges are highly sought after. In summary, despite the failure to rationalize cautiousness in the one-type rational model, the levels of estimated curvature in both models are consistent with anecdotal evidence on the perceived importance of competitiveness/cutoffs on college prestige.³⁴

Out-of-sample prediction of the mixture model is also substantially better than the one-type rational model. 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. As demonstrated in Panel B of Table 5, compared to the one-type rational model, the mixture model decreases the distance 14.9%, 43.4%, and 47.2%, respectively, and fits much better

³³The 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 sample size. The criteria favor smaller value.

³⁴Table B6 reports the full set of estimated parameters.

in the moments that are related to our predictions about cautiousness and reversals.

Quantitatively, the contribution of the DC decision rule to the fit is more robust across models that allow for different degrees of preference heterogeneity. To quantify this point, Panel A reports specifications where we keep all model setup the same as in Table 5, except that we assume away across-type preference heterogeneity and take into account only preferences over competitiveness and distance. The numbers of parameters for each subsample, as a result, drop from 20, 29 to 8, 11, respectively. We find that the fit with the DC Type, despite having merely three more parameters, still improves the fit by 60.6%, 54.6%, and 57.2%, respectively. More strikingly, if we compare the even columns in Panel A, Table 6 to the odd columns in Table 5, the fit of the mixture model, despite having less flexibility in preferences and fewer parameters, is also much better than the one-type model in benchmark estimation (distance decreases by 40.4%, 40.5%, and 34.5%, respectively). The estimates on the share of the DC Type remain precisely estimated and stable, where the estimated share is 49.3% (SE=0.25%), 47.8% (SE=0.23%), 54.0% (SE=0.30%) respectively.

To further understand how the model fits the data, we look at the key moments that identify the presence of the DC Type. Figure 8 compares the overall data and fit from the one-type rational model and the mixture model, for average admission probability (Figure 8a) and share of reversals with different thresholds (Figure 8b), 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 probability is around 90% for the fourth choices. Moreover, the one-type model also fails to match the share of reversals when the threshold is low, which further differentiates itself from the mixture model in terms of fit. Under this parametrization, an implausible level of curvature or horizontal preferences would substantially worsen the fit of other moments. As an example of how arbitrary preferences could worsen the fit overall, Figure 8c shows that both models yield a correlation of 0.9, whereas in Section 4.3 we show that simulated correlation decreases to 0.8 or even lower if we introduce more curvature or horizontal preferences. While our model does not directly fit the empirical data on upward movements, Figure 8d shows that, consistent with our theory, the estimated upward movement coefficient γ obtained by running regression 6 on the simulated sample generated the estimated mixture model, is uniformly higher compared to that generated by the rational one-type model. Consequently, the mixture model generates upward movements that are closer to the patterns we observe in the data ³⁵.

In Figure A9 we compare the prediction of the mixture model for the most and least advantaged quartile to the data. Similarly to the empirical exercise in Section 4, we reweight to control for priority scores. While the fit is not perfect, the comparative statics are consistent with our expectation. The predicted cautiousness for the first choices is indeed more evident among the

³⁵Table B10, B13, B16 report the fit of one-type rational model for all moments by the quintile of priority scores. Table B11, B14, B17 report the fit of one-type rational model for all moments by the quintile of priority scores.

disadvantaged, and the predicted gap is less for other choices, consistent with the data. In terms of reversal, the predicted share is higher among the disadvantaged, in line with the data.

7.5 Welfare

We compare the admission outcomes in our data to a counterfactual where all the behavioral applicants have been de-biased and play optimally, as well as counterfactual scenarios where behavioral applicants continue to use the DC decision rule under other mechanisms. This investigation is helpful for the analysis of the distributional consequences of suboptimal decision-making (Pathak and Sönmez, 2008), and potentially helpful for policy discussion. To compute the counterfactual, we follow Kapor et al. (2020) to simulate how everyone, if rational, would react to the current equilibrium (distribution of cutoffs). We thereby obtain new lists. Then, the program uses the new lists to simulate the cutoffs, and iterate until the cutoffs converge.

The money metrics of welfare is motivated by the analogy that students' priority scores (determined by their exam performance, not college demand or their strategy) serve as their WTP for college education, and that cutoffs of the colleges serve as the prices of such service. We treat students' priority scores as students "budget set", and measure the welfare change as the equivalent variation (EV) in terms of priority score. In other words, for each individual applicant, 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 but a new equilibrium happened. We take this approach for two reasons. First, the estimation results suggest that priority score is an effective measure of student ability, and cutoff is a good predictor of college quality. Second, common measures such as physical distance contradict strong geographical preferences toward economically developed area in China, which are all very far from Ningxia.

De-Biasing: Teaching Students to Correctly Approach the Problem If all students had the same cardinal preferences, the matching process would be a zero-sum game. Conventional wisdom suggests that the sophisticated usually take advantage of the naive in a market setting (Gabaix and Laibson, 2006; Pathak and Sönmez, 2008). However, even without horizontal preferences, the intensity of vertical preferences may actually differ, and acting strategically in the correct way will help students communicate such intensity and improve equilibrium outcomes (Abdulkadiroğlu et al., 2011). It is an empirical question whether students' preference profile in our case would lead to different distributional implications of de-biasing. We report our finding in Panel C of Table 5. De-biasing improves the 3rd, 4th and 5th quintile of the DC Type's welfare, which is equivalent to an improvement of 0.495, 0.253, 0.082 of a standard deviation (s.d.) 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 quintile by 0.368 and 0.217 s.d. of the score, and decreases the welfare of those whose scores belong to the highest quintile by 0.080. These result suggest that, far from a zero-sum game, de-biasing benefits the vast majority of students except for the most advantaged rationals at the top of priority score distribution. Intuitively, this happens because, in

the old equilibrium, the behavioral type creates a mismatch effect by affecting the rational counterparts whose priority score is lower. De-biasing eliminates this effect, and benefits any rational type whose score is not high enough that he or she is immune to the impact of the mistaken choices due to behavioral type decision-making.

DAA with Unlimited List DAA that allows applicants to list an unlimited number of choices restores the strategy-proof property of the mechanism, such that the mistakes in strategic play are no longer relevant. However, it has an additional effect that students can no longer express their preference intensity through strategic play. We report the welfare effect of adopting a strategy-proof property in Panel C. A DAA mechanism with an unlimited list decreases the welfare of the rationals in the 3rd, 4th, and 5th quintiles by 0.329, 0.725, and 0.045 s.d. of score. It increases the welfare of the DC Type in the 3rd and 4th quintile by 0.231 and 0.447 s.d. of score, but decreases the welfare of the DC in the 5th quintile by 0.155 s.d. of score. Overall, switching to a strategy-proof mechanism is not welfare enhancing for the majority of the students. Note that empirically the finding here resembles previous studies (Agarwal and Somaini, 2018; Calsamiglia et al., 2020). An important caveat is that such evaluation ignores a potential benefit that, under unconstrained DAA, mistaken beliefs about admission probability are no longer costly (Kapor et al., 2020).

Manipulable Mechanisms Compared to the constrained DAA in our setting, the Boston mechanism is more manipulable. Different from the case of Pathak and Sönmez (2008), however, the behavioral bias we document is less costly under the Boston mechanism because it weakens the rational type’s advantage of using backup choices as “insurance” to act aggressively for their top choices. Because the behavioral type doesn’t know how to take this advantage, switching to Boston mechanism might decrease the welfare inequality between these two types. However, as reported in Panel C, our results suggest that switching to the Boston mechanism leads to a decrease in welfare ($0.02 \sim 0.15$ s.d. of score) for students of both types, in the 3rd, 4th and 5th quintiles, although the decrease for the DC Type is indeed 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)’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, despite a substantial share of applicants who do not understand the option value brought about by the backup bottom choices. This is because the mechanism in our setting reduces the cost of miscoordination (Chen and Kesten, 2019), while preserving students’ ability to communicate their preference intensities via strategic play.

Inequality Figure 9 presents how de-biasing and mechanism switching differentially 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 score, and the welfare

increase for the most advantaged quartile is equivalent to 0.221 s.d. of score. This finding could be explained by the fact that the estimated share of the DC Type is higher among the disadvantaged. Consequently, given the estimated preferences, de-biasing outperforms alternative mechanisms in both equity and efficiency.

Effect of De-Biasing on Outcome Gap in terms of Selectivity Section 4.4 have discussed the finding that conditional on students’ priority scores, the most socio-economically disadvantaged quartile ends up in less selective colleges compared to their advantaged counterparts, and the gap amounts to 0.1288 standard deviation. In light of this, another measure that could tell us the quantitative impact of the behavioral bias that we document is to examine whether de-biasing would shrink the observed gap. In the structural model, this gap is explained by other differences in college preferences, or the behavioral biases. Thus the estimated gap under the counterfactual scenario where all students are de-biased tease out the portion of the gap that is attributable to differential preferences, in the absence of the behavioral biases. We conduct exactly the same regression analysis as discussed in Section 4.4, on the data that is simulated by the estimated preferences, under the assumption that all students are acting optimally. We report the results in Table B3, Panel B. The drastic shrinkage in gap suggests that in this particular structural model at least 83.15% of the observed gaps in college selectivity can be explained by the behavioral biases, rather than heterogeneous preferences across students of socio-economic status.

8 Alternative Considerations

8.1 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 0.5034. 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 B5, students on average overestimate the chance of admission by 11.3%, and the mean of absolute error is 30.6%.

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 $\mu_{\tau_0} = 11.3\%$ and $\mu_{\tau_1} = 2.17\%$ is taken from results in Table B5. $\mu_{\tau_2} = -0.896$ 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 significantly across students of different SES status.

In Panel B of Table 6, we consider the impact of heterogeneous beliefs about admission probability on our estimation. We re-run the same specifications in Table 5. 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% ~ 60%, 60% ~ 80%, 80% ~ 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 5, 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. ³⁶

8.2 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 independence 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.

³⁶Table B7 reports the full set of estimated parameters with heterogeneous beliefs. Table B18, B20, B22 report fit of the one-type rational model. Table B19, B21, B23 report fit of the mixture model.

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, $\hat{\alpha}_2 = 0.0033$ (SE=0.0037) and -0.0094 (SE=0.0060) for the science and humanity tracks, respectively, whereas $\hat{\beta}_2 = 0.9883$ (SE=0.0060) and 1.0252 (SE=0.0107) for the science and humanity tracks, respectively. The p-values of the F-test are 0.085 and 0.059, respectively, meaning that we fail to reject the null hypothesis.

8.3 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 switching³⁷. 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 B8. 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 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.

9 Discussion and Conclusion

We provided evidence that, when a centralized admission system incentivizes strategic reporting, such that the optimal decision rule is complex, a substantial share of student applicants engage in a myopic strategy of risk taking in a way that can be well explained by the theory of directed cognition. Our estimation also suggests that the DC Type is particularly concentrated among disadvantaged students, and is responsible for the worse admission outcomes among the disadvantaged compared

³⁷The link [here](#) is an example. Since this campaign by the MoE, major distinctions have become more coarse and less of a concern to students.

to their advantaged counterparts who achieve the same level of CEE score, exacerbating inequality in educational attainment. In a counterfactual analysis, de-biasing the DC Type substantially increases the welfare for the behavioral type and, surprisingly, for the majority of the rational type, by enhancing matching efficiencies; it outperforms alternative mechanisms (e.g. Boston and Deferred Acceptance mechanism without list constraint) in terms of both equity and efficiency.

The DC decision rule could be applied to other contexts or mechanisms where the optimal response necessitates processing risk and uncertainty that unravel in multiple stages. Our paper provides empirical methods to identify systematic departures from optimality for ROL data, where heterogeneous preferences typically make such investigation difficult. Our findings suggest that behavioral bias plays a role in inequality formation. To address such imperfections in decision making, it may sometimes be more desirable to intervene against the bias itself, rather than changing the mechanism altogether. We hope that more empirical research will be conducted in other contexts to uncover the broad picture of potential sub-optimality in a complex decision-making environment.

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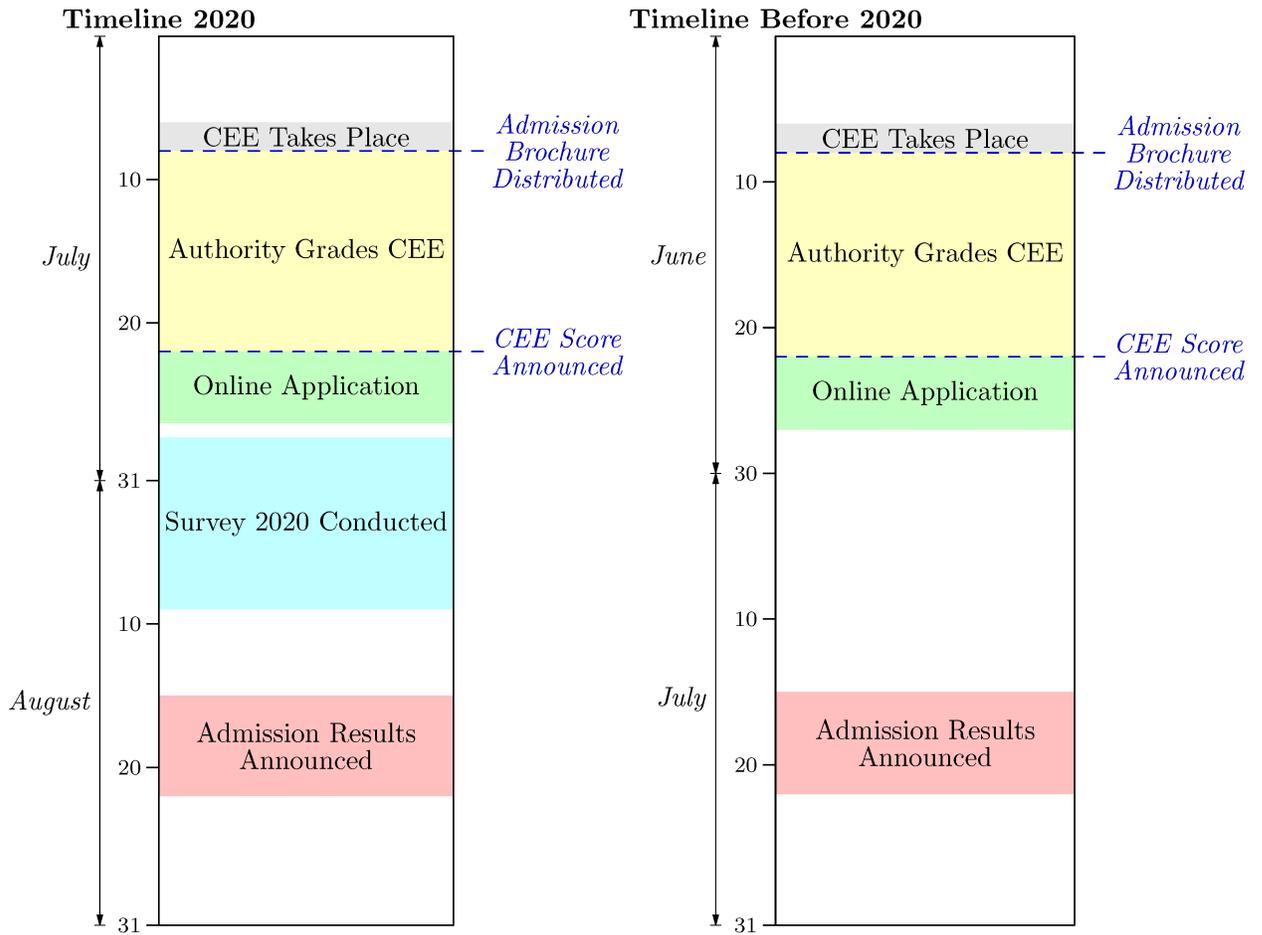
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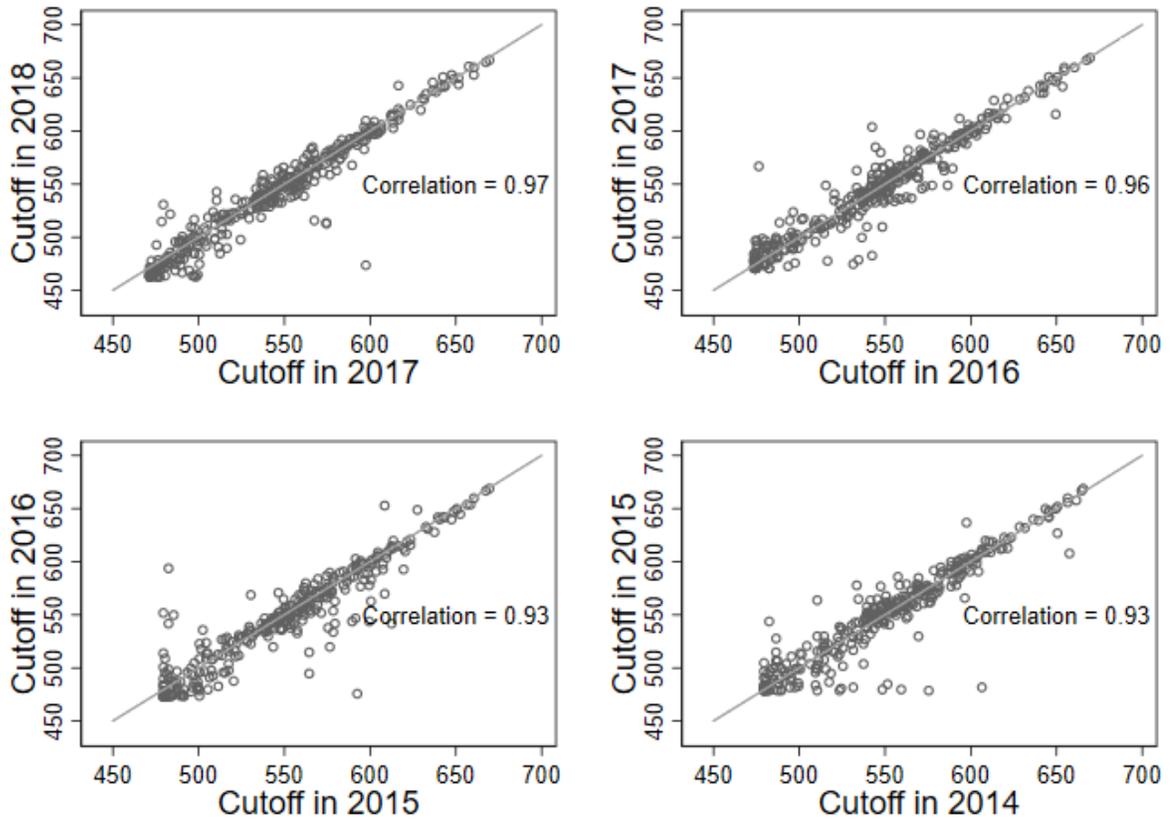
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Figure 1: Timeline of College Admission Process



Note: This figure presents the timeline of college admission process, as detailed in Section 2.1, 2.2, 2.3. 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.

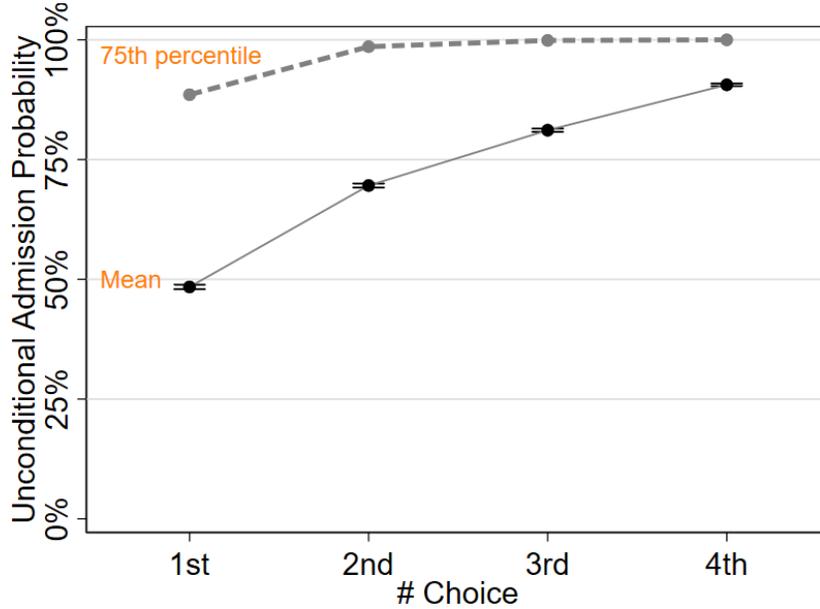
Figure 2: Admission Cutoffs Across Years



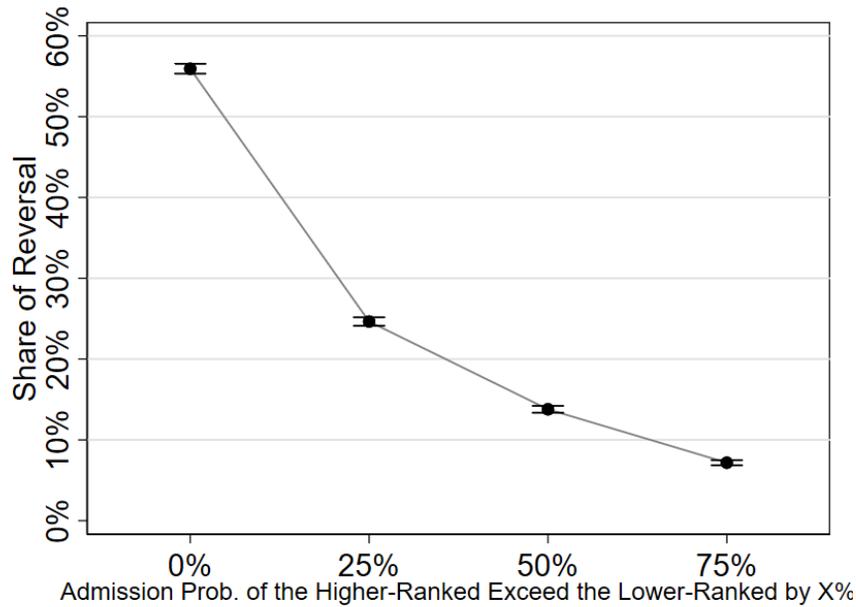
Note: This figure plots the admission cutoffs for all colleges that admit Ningxia students during 2014-2018, for the discussion in Section 3.2. The admission cutoffs are converted to its 2018 rank-preserving equivalents. Each dot represents the admission cutoffs of a specific college in two consecutive 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 3: Summary Statistics of Unconditional Admission Probability

(a) Admission Probability: Mean & 75th Percentile for Each Position

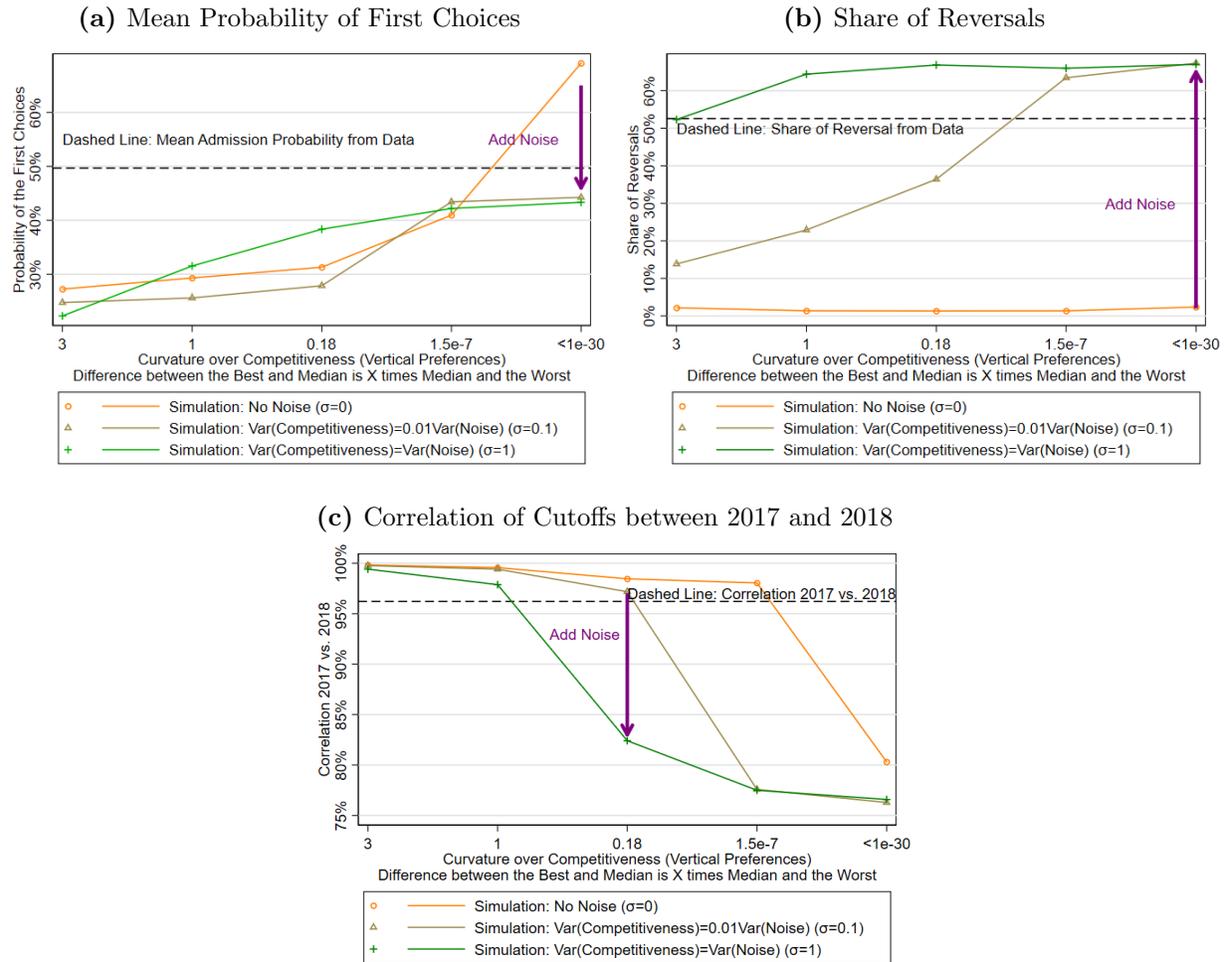


(b) Share of Risk-Taking Reversals



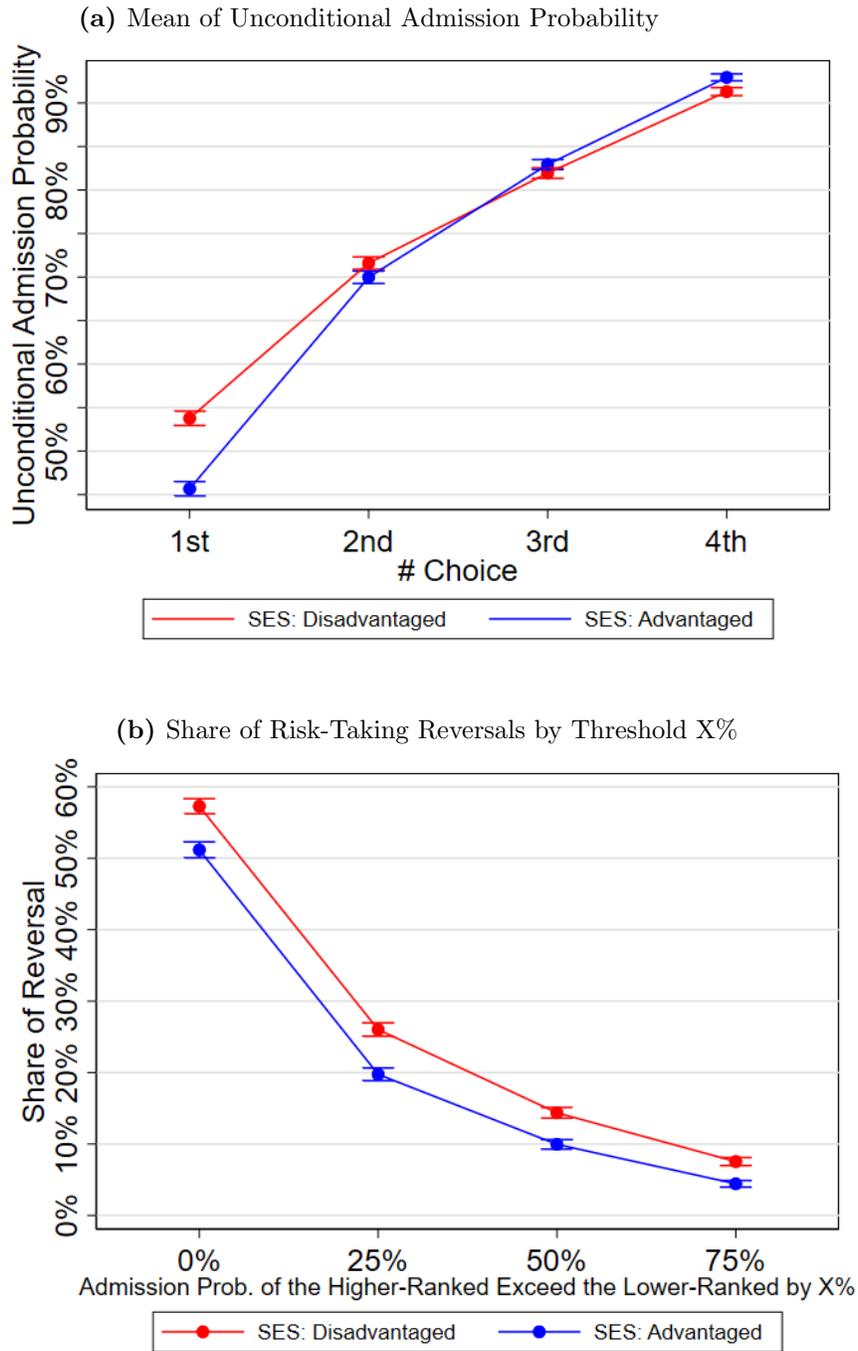
Note: The figure presents summary statistics of unconditional admission probability that are related to the the discussion in Section 4.2. Subfigure (a) is a box plot that presents the mean and 75th percentile of the estimated unconditional admission probability for the four choices respectively. Subfigure (b) concerns the share of students whose lists exhibit at least one pair of risk-taking reversals, defined as ranking a less-selective college above a more-selective college on the ROL. We compute the share as a function of the threshold above which the reversal is counted. The higher the threshold is, the less reversals that are serious enough to be counted in the statistics. Mathematically, 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.

Figure 4: Simulation vs. Data: Cautiousness, Reversals, and Correlation of Cutoffs



Note: This figure compares the value of empirical and simulated moments along the dimension of first choices and risk-taking reversals among students whose priority scores are top 60%, for the discussion in Section 4.3. In subfigure (a), the vertical axis is the average of unconditional admission probability of first choices. In subfigure (b), the vertical axis is the share of students whose ROL has a reversal pair of which the unconditional probability of the higher-ranked is larger than the lower-ranked. In subfigure (c), the vertical axis is the correlation of cutoffs in 2017 and 2018 for all colleges. The horizontal axis in all subfigures is the curvature over college competitiveness as measured by average normalized cutoffs during 2014-2018, which is controlled by ρ . Solid line and dashed line in both figures represent simulated moments and data, respectively. For simulated moments, we simulate each applicant's choices 50 times and take the average over the whole relevant sample. Hollow circles in orange represent the simulated moments where no noise is added ($\sigma = 0$). Hollow triangles in brown represent the simulated moment where small scale noise is added ($\sigma = 0.1$). Plus signs in green represent the simulated moments where substantial noise is added ($\sigma = 1$)

Figure 5: Mean of Admission Probability and Share of Reversals by SES Groups



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 4.4. Subfigure (a) plots the mean of unconditional admission probability. Subfigure (b) plots the share of students whose strategy exhibits at least one pair of risk-taking 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 6: 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>40	Somewhat Cautious 30<L≤40	Risk Tolerant L≤30	Total
ROL 1st Choice: Payoff of non-first colleges is 20 CNY. Indifferent Between (25 CNY, 50%) (R CNY, 25%)	Very Cautious	R>40	281 19.9%	631 44.7%	62 4.4%	974 69.0%
	Somewhat Cautious	30<R≤40	20 1.4%	289 20.5%	39 2.8%	348 24.7%
	Risk Tolerant	R≤30	3 0.2%	48 3.4%	39 2.8%	90 6.4%
	Total		304 21.5%	968 68.6%	140 9.9%	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 5.3.

Blue cells indicate that students' responses are roughly consistent in the "ROL first-choice" problem and the standard lottery problem, as predicted by Rational Decision Rule.

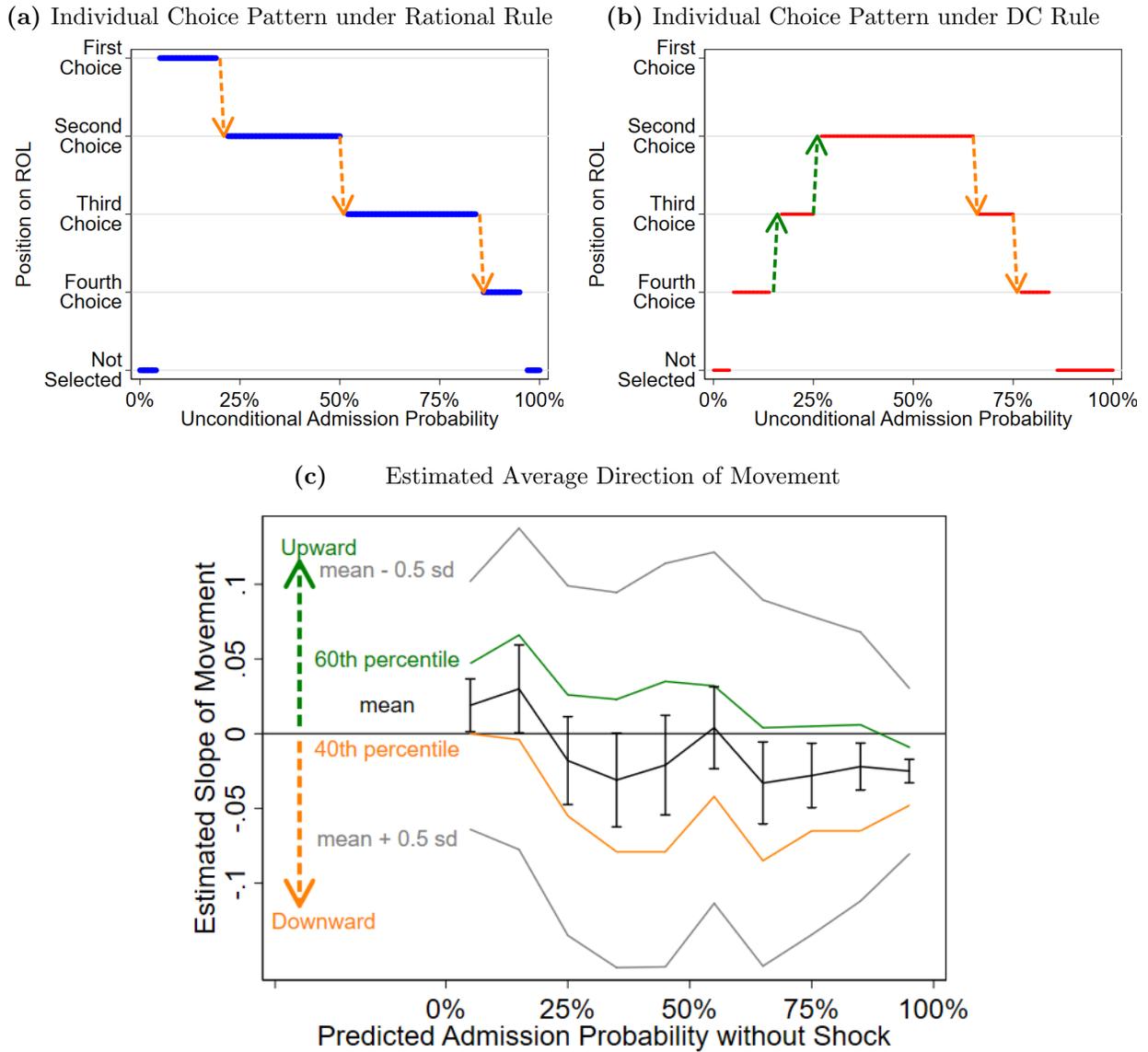
Red cells indicate that students' responses are more cautious in "ROL first-choice" problem, as predicted by Directed Cognition (DC) Decision Rule.

Gray cells indicate that students' responses are less cautious in "ROL first-choice" problem, which cannot be predicted by either 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.

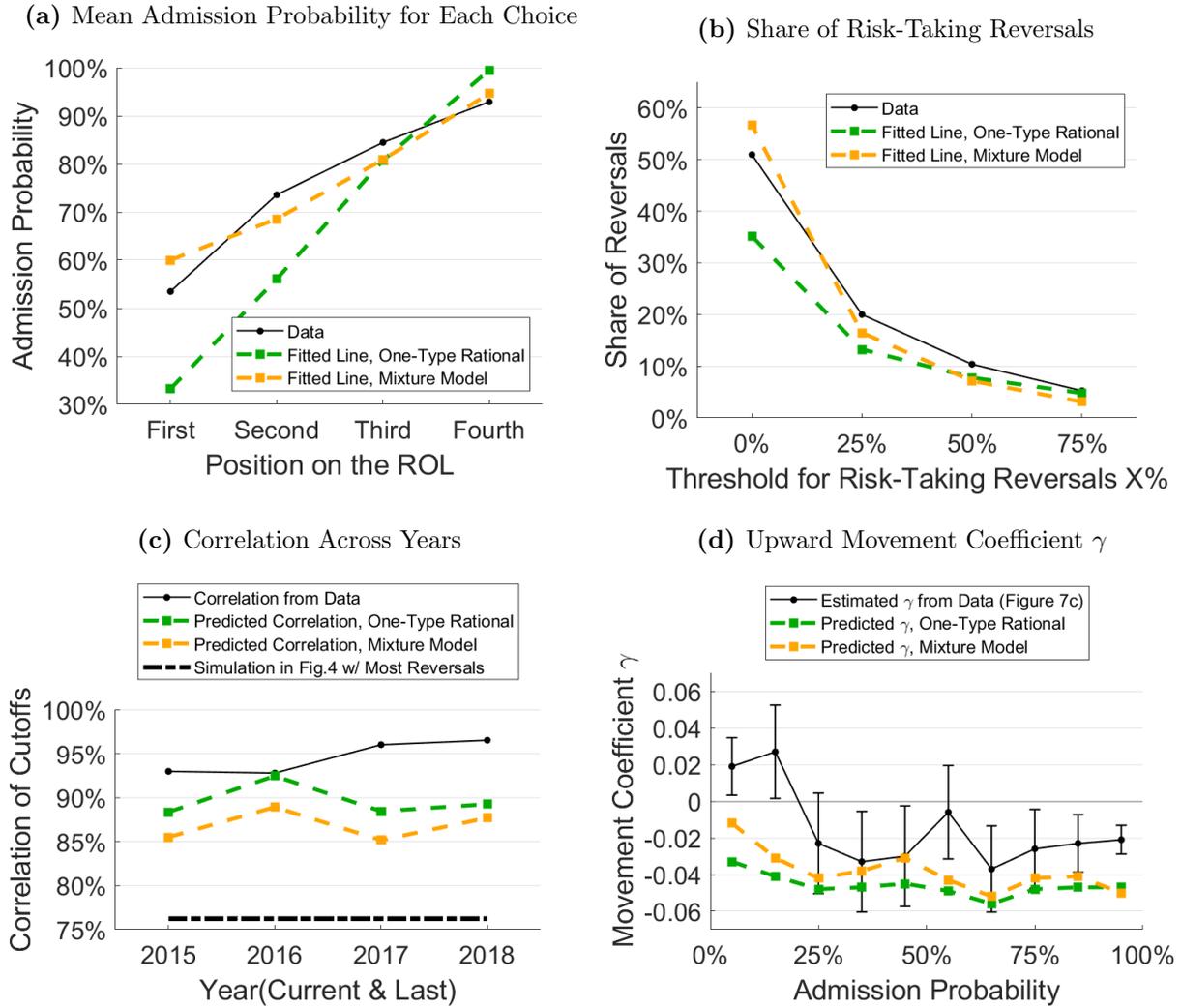
"Equivalent Lottery" question (horizontal) corresponds to Question Group 2. In this question, students need to choose from lottery X, whose payoff is 25 CNY with 50% of chance, 20 CNY with 50% of chance, or lottery Y, whose payoff is L CNY with 25% of chance, 20 CNY with 75% of chance, where $L = 30, 35, 40, 45, 50, 55, 60$, respectively. Note that "Equivalent Lottery Question" is mathematically equivalent to the aforementioned "ROL first-choice Question".

Figure 7: Prediction: Position Movement in ROL as Priority Score Changes



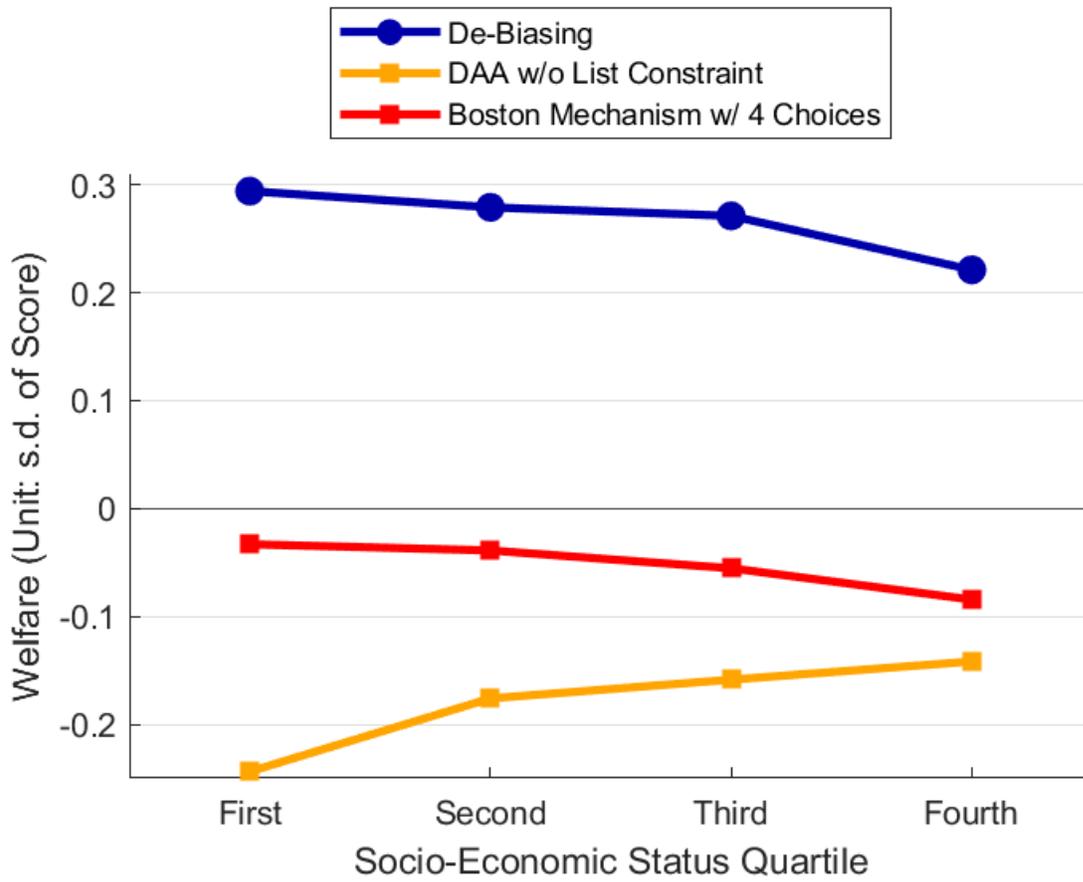
Note: This figure shows the prediction about how any single college move on the list as priority score changes under Rational Decision Rule and DC Decision Rule respectively, as discussed in Section 6.1, and 6.3. Subfigure (a) presents an example where the college in question is put on the list under 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 \pm 0.5sd of slope for each probability bin using the regression described in 6.3.

Figure 8: 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 risk-taking reversals where the unconditional probability of the higher-ranked exceeds that of lower-ranked by more than X%. Subfigure (c) plots the correlation of simulated cutoffs across years. For example, 2015 means that the statistics concerns the correlation between 2014 cutoffs and 2015 cutoffs. Figure (d) compares the estimated upward movement index, that is, the γ we obtain by running regression 6, from Figure 7c and Table 4.

Figure 9: 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

	(1)	(2)	(3)
Unconditional Admission Probability	First	Fourth	Fourth-First
Panel A: Estimated Coefficient			
Most Disadvantaged Quartile	6.74%*** (0.70%)	-2.24%*** (0.40%)	-8.98%*** (0.78%)
Benchmark Group	Most Advantaged Quartile		
Predicted Mean: Most Advantaged	44.58% (0.43%)	92.11% (0.24%)	47.53% (0.48%)
Panel B: Predicted Mean of Disadv-Adv Gap, by Quartile of Priority Score			
E[Adv-Disadv Priority Score 40%]	5.77% (0.96%)	-1.66% (0.54%)	-7.43% (1.08%)
E[Adv-Disadv Priority Score 60%]	7.72% (0.87%)	-1.97% (0.49%)	-9.69% (0.97%)
E[Adv-Disadv Priority Score 80%]	10.36% (1.67%)	-1.88% (0.94%)	-12.23% (1.87%)
E[Adv-Disadv Priority Score 99%]	8.76% (5.94%)	-3.72% (3.37%)	-12.48% (6.65%)
Panel C: List of Controls			
4th-Order Polynomial of Priority Score	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Track (Science or Humanity) Fixed Effects	Yes	Yes	Yes

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 4.4. All statistics 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. 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 main effect of belonging to the most disadvantaged. Panel B examines the heterogeneity of adv-disadv gap by reporting the predicted mean of gap conditional on priority score quartile. Panel C reports the additional controls. All statistics are in their percentage form * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 2: Risk-Taking 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: Estimated Coefficient				
Most Disadvantaged Quartile	5.55%*** (0.94%)	6.64%*** (0.80%)	4.97%*** (0.64%)	3.91%*** (0.48%)
Benchmark Group	Most Advantaged Quartile			
Predicted Mean of Benchmark Group	53.12% (0.57%)	21.43% (0.49%)	11.13% (0.39%)	4.94% (0.29%)
Panel B: Predicted Mean of Disadv-Adv Gap, by Quartile of Priority Score				
E[Adv-Disadv Priority Score 40%]	6.71% (1.28%)	7.10% (1.10%)	6.00% (0.87%)	5.79% (0.65%)
E[Adv-Disadv Priority Score 60%]	4.87% (1.16%)	5.89% (0.99%)	4.24% (0.79%)	3.05% (0.59%)
E[Adv-Disadv Priority Score 80%]	3.36% (2.23%)	4.31% (1.90%)	2.23% (1.51%)	0.27% (1.13%)
E[Adv-Disadv Priority Score 99%]	9.78% (7.94%)	8.40% (6.79%)	4.31% (5.4%)	1.58% (4.04%)
Panel C: 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

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 4.4. 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. All statistics 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 A reports the main effect of belonging to the most disadvantaged. Panel B examines the heterogeneity of adv-disadv gap by reporting the predicted mean of gap conditional on priority score quartile. Panel C reports the additional controls. All statistics are in their percentage form * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3: Testing Framing Effect - Incentivized Survey Responses

<i>Panel A: Response Inconsistency Between ROL and Lottery Question</i>			
	(1)	(2)	(3)
	ROL 1st Choice: Payoff of non-1st colleges is 20 CNY. Indifferent Between (25 CNY, 50%) & (R CNY, 25%) Equivalent Lottery: Indifferent Between (25 CNY, 50%; 20 CNY, 50%) & (Y CNY, 25%; 20 CNY 75%) Inconsistency Measure: R-Y		
SES Index Normalized	0.884*** (0.226)	0.817*** (0.234)	0.804*** (0.286)
Mean of Inconsistency		10.166 (0.313)	
Control: Priority Score	Yes	Yes	Yes
Control: Demographic Variables	No	Yes	Yes
Control: College Preferences	No	No	Yes
R squared	0.023	0.032	0.093
Observations	1412	1412	1412
<i>Panel B: Estimated Share of Type and Risk Preferences from Survey Responses</i>			
	(1)	(2)	(3)
Share of Directed Cognition Type: Mean	0.0% -	49.8% (1.8%)	48.7% (1.8%)
Marginal Effect of Normalized SES	0.0% -	-7.0% (1.9%)	-7.3% (1.7%)
Marginal Effect of Normalized Score	0.0% -	-3.8% (1.5%)	-4.0% (1.5%)
Share of Sincere Type	0.0% -	0.0% -	3.1% (0.5%)
CRRA Risk Coefficient: Mean	0.239 (0.013)	0.056 (0.014)	0.079 (0.013)
CRRA Risk Coefficient: SES	-0.013 (0.012)	0.010 (0.015)	0.010 (0.013)
CRRA Risk Coefficient: Normalized Score	-0.016 (0.013)	-0.009 (0.012)	-0.011 (0.011)
Number of Parameters	6	9	10
Log Likelihood	-6271.152	-5770.302	-5733.326
Number of Observations	1412	1412	1412
Bayesian Information Criterion	12585.82	11605.88	11539.18

Note: This table reports empirical analysis from incentivized survey response, as described in Section 5.3. Panel A analyzes to what extent the inconsistency of risk-taking across “ROL 1st Choice” question and “Equivalent Lottery” question 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 as theorized in [Pathak and Sönmez \(2008\)](#).

Table 4: 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 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% ~ 10%, 10% ~ 20%, 20% ~ 30%, ..., 80% ~ 90%, 90% ~ 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 6 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 and standard error of the mean of the score shock μ_γ (Column 2), estimated standard deviation of the slope for the score shock σ_γ (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 5: Structural Estimation of Mixture Model using Administrative Data

<i>Panel A: Estimation Results - Rational One-Type vs. Mixture Model</i>						
Sample (Quantile of Priority Score) Model	(1)	(2)	(3)	(4)	(5)	(6)
	40%-60%		60%-80%		80%-100%	
	Rational	Mixture	Rational	Mixture	Rational	Mixture
Estimated Share of DC Type		53.1% (0.61%)		45.1% (0.54%)		55.1% (0.55%)
Marginal Effect of SES		-3.71% (0.57%)		-3.68% (0.56%)		-6.02% (0.55%)
Mean Curvature: Rational Type	-0.044 (0.007)	-0.375 (0.027)	0.413 (0.022)	-0.365 (0.024)	0.307 (0.014)	-0.336 (0.021)
Mean Curvature: DC Type		-0.486 (0.055)		-0.459 (0.033)		-0.478 (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
<i>Panel B: Out-of-Sample Predictions - Rational One-Type vs. Mixture Model</i>						
Sample (Quantile of Priority Score) Model	40%-60%		60%-80%		80%-100%	
	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%
<i>Panel C: Welfare Evaluation Using Mixture Model (Unit: Standard Deviation of Priority Score)</i>						
Sample (Quantile of Priority Score) Type	40%-60%		60%-80%		80%-100%	
	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% ~ 60% (column 1,2), 60% ~ 80% (column 3,4), and 80% ~ 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.

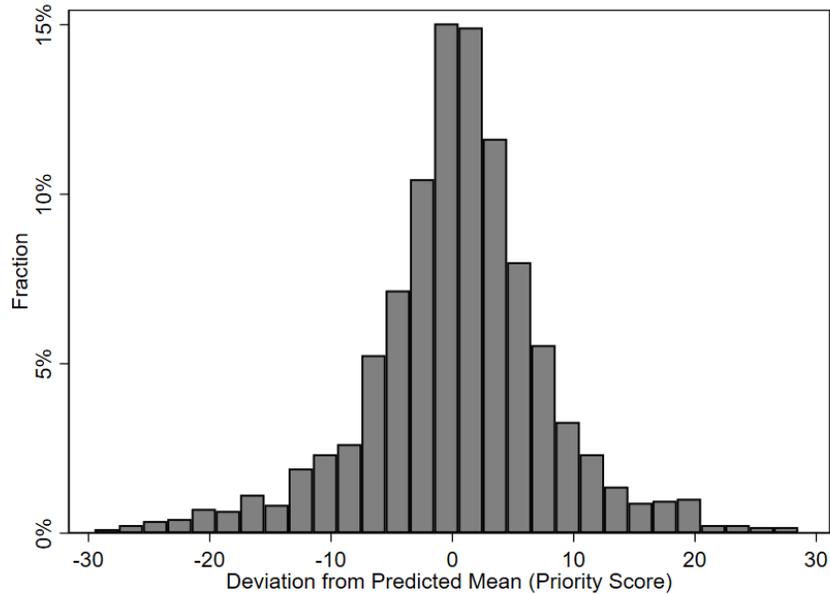
Table 6: Alternative Specifications of Structural Estimation

Panel A: Alternative Specifications - Less Flexible Preferences						
Sample (Quantile of Priority Score)	(1)	(2)	(3)	(4)	(5)	(6)
	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

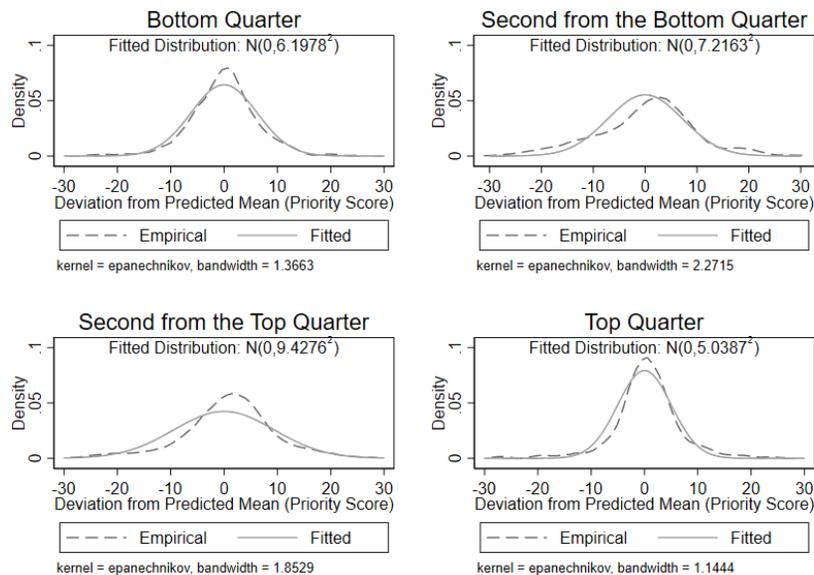
Note: This table reports the results of structural analysis as described in Section 7.4 and 8.1, for the 40% ~ 60% (column 1,2), 60% ~ 80% (column 3,4), and 80% ~ 100% (column 5,6) subsample using alternative specifications. Panel A reports the estimation results where the model is the same as the single-type/mixture model in Table 5 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 5 but we additionally introduce perturbation in beliefs with the parameters of the perturbation distribution calibrated using data from the online survey.

A Supplementary Figures

Figure A1: Distribution of Realized Cutoff-Predicted Mean Differences



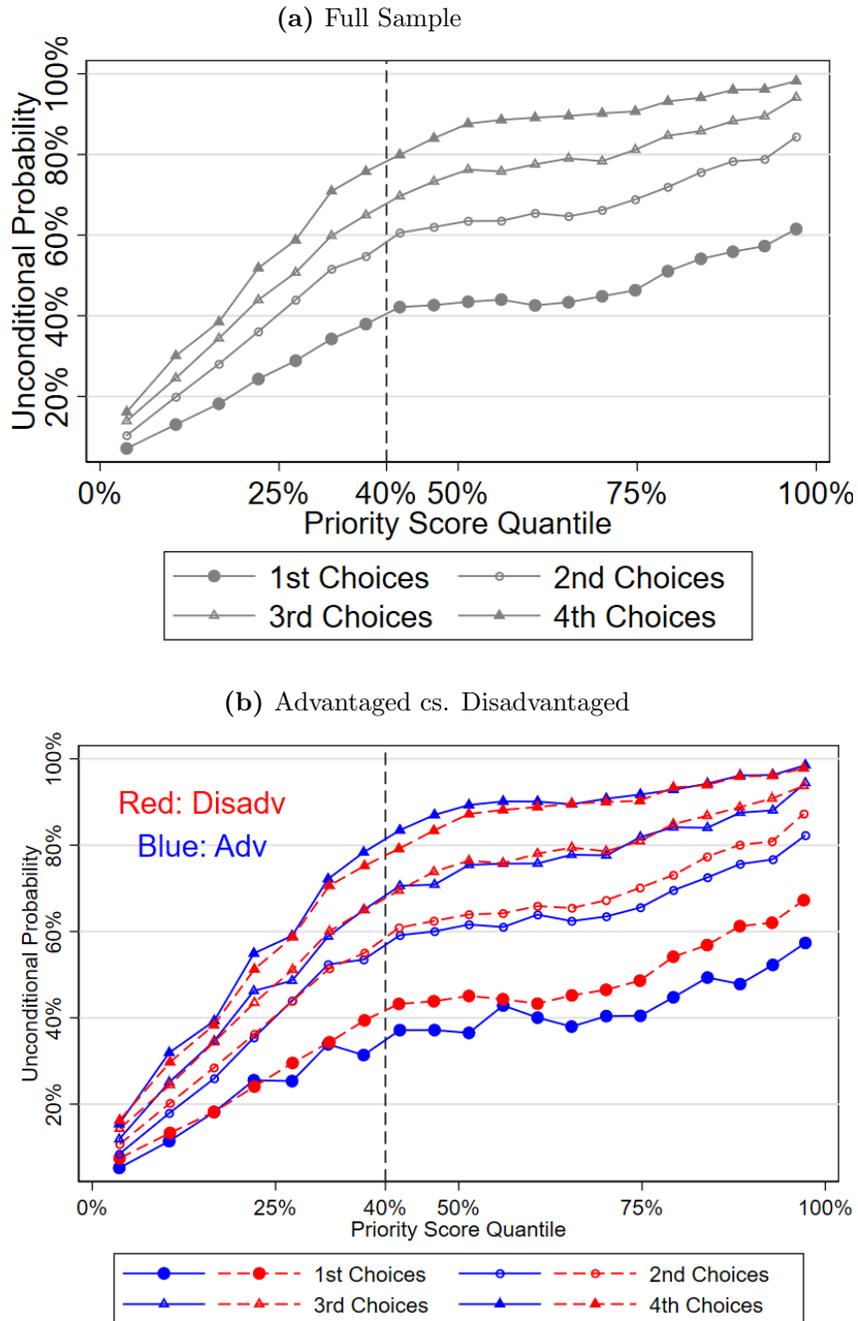
(a) Distribution of Differences: All Colleges



(b) Distribution of Differences by College Competitiveness

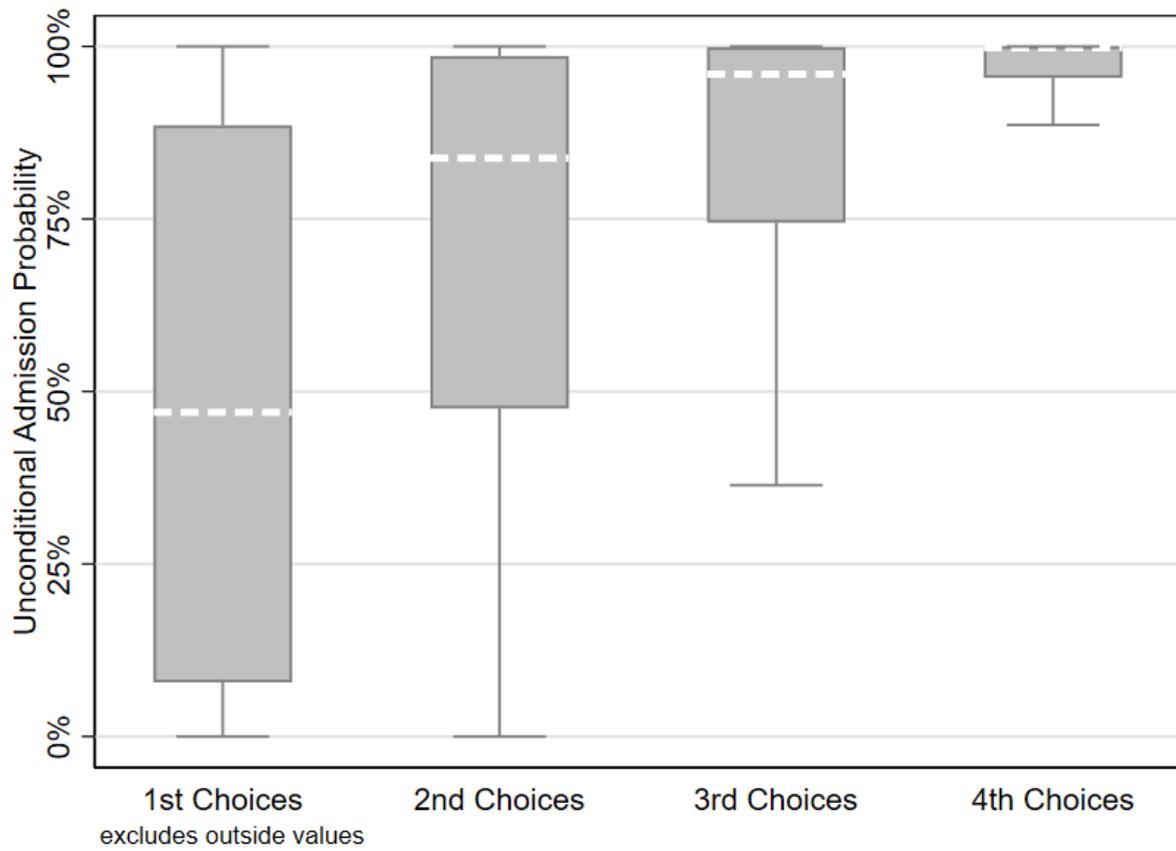
Note: This figure plots the distribution of distance between realized cutoffs and predicted mean as defined in Section 3.2. Subfigure (a) plots the distribution of differences between admission cutoffs and predicted mean among all colleges. Subfigure (b) plots the distribution of differences by college 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, 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 A2: Mean of Admission Probability Conditional on Priority Score



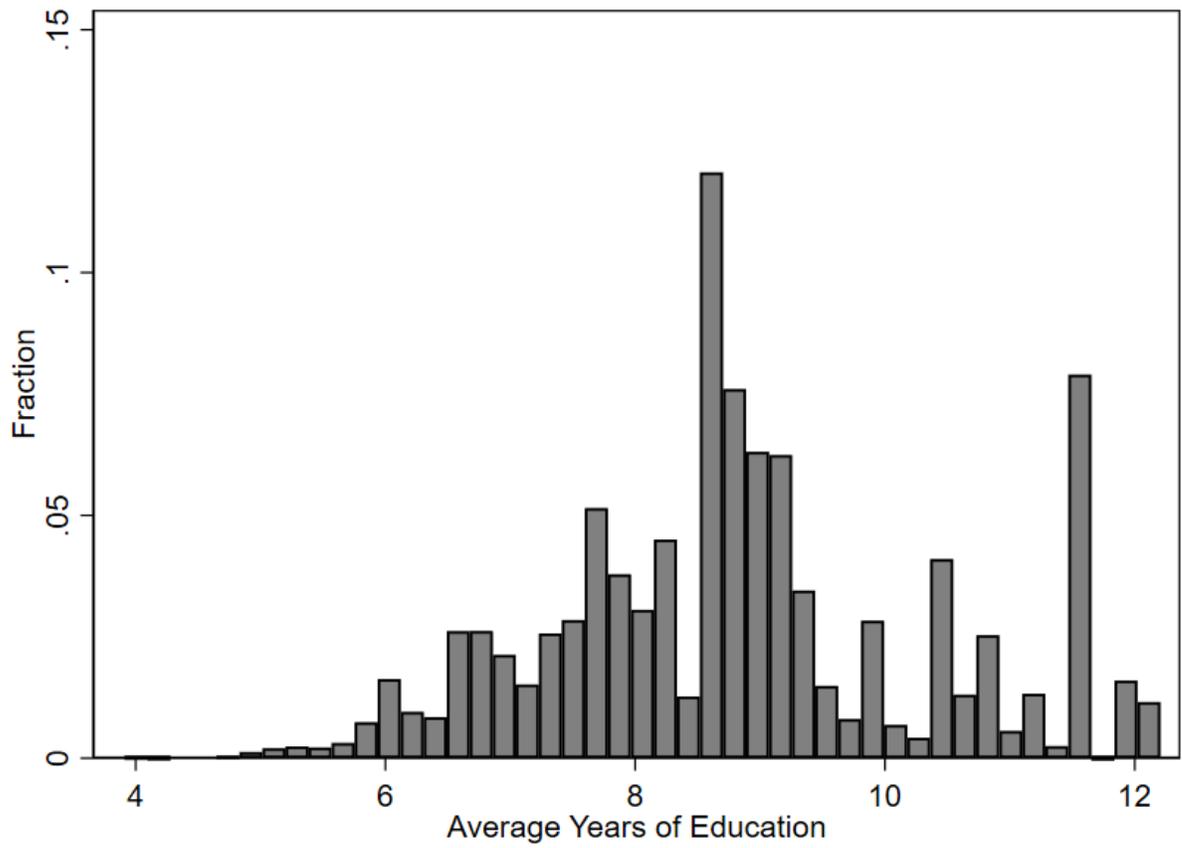
Note: This figure plots the mean of admission probability conditional on the quantile of priority score for student applicants' first choices, second choices, third choices and fourth choices, respectively. Subfigure (a) plots the statistics for the entire sample. Subfigure (b) plots the statistics for 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 A3: Box Plot of Distribution of Admission Probabilities for the Four Choices



Note: This figure presents the standard box plots of the distribution of admission probabilities for the four choices. The statistics is relevant for discussion in Section 4.2.

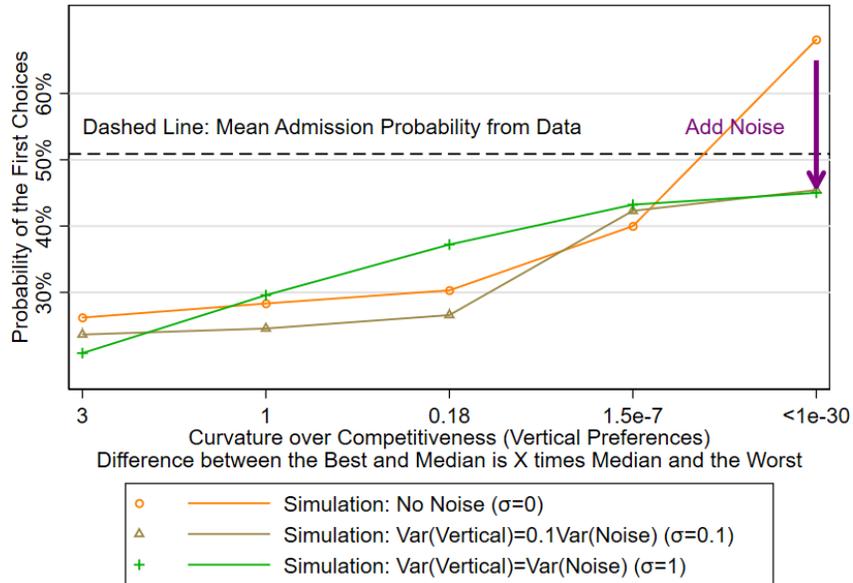
Figure A4: Average Years of Education in Administrative Data (Township Level)



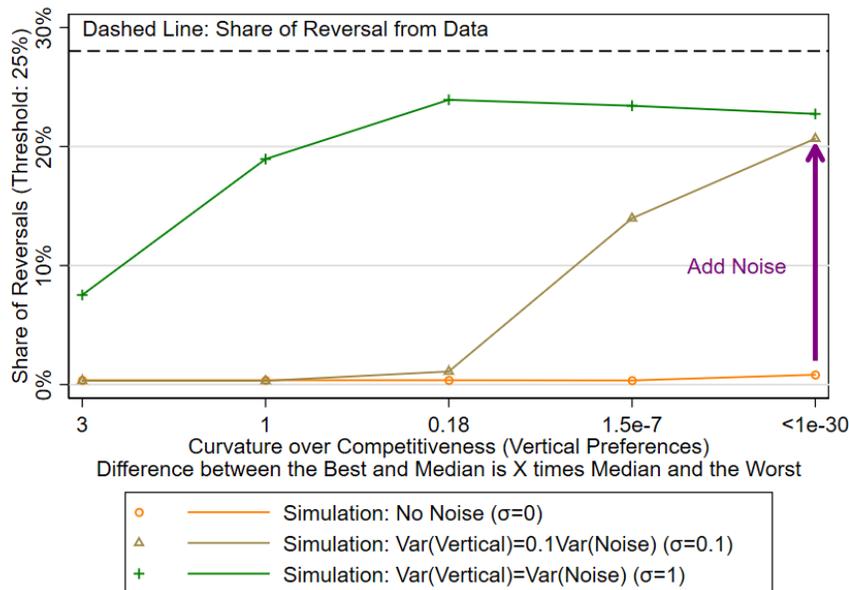
Note: This figure plots the cumulative distribution of probability of meeting cutoffs for students' first (in red), second (in yellow), third (in green) and fourth (in blue) choices, respectively, during 2014-2018. This graph is helpful for the discussion in Section 4.4.

**Figure A5: Simulation vs. Data: Probability of First Choices and Share of Reversals
The Most Disadvantaged Quartile**

(a) Mean Probability of First Choices

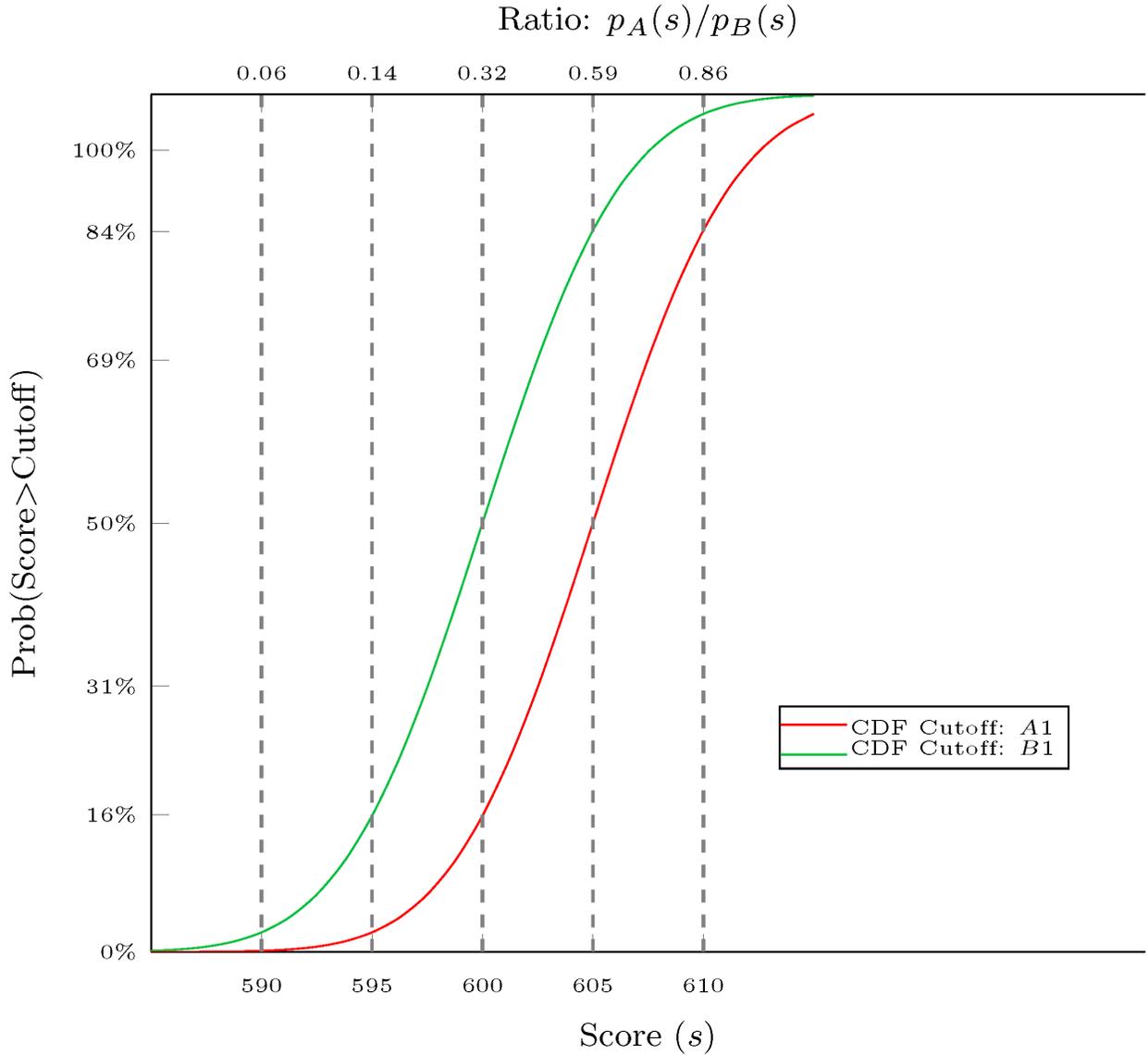


(b) Share of Reversals



Note: This figure compares the value of empirical and simulated moments along the dimension of first choices and risk-taking reversals among students whose priority scores are top 60%, and are from the most disadvantaged quartile. In subfigure (a), the vertical axis is the average of unconditional admission probability of first choices. In subfigure (b), the vertical axis is the share of students whose ROL has a reversal pair of which the unconditional probability of the higher ranked is at least 25% larger than the lower-ranked. The horizontal axis in all subfigures is the curvature over college competitiveness as measured by average normalized cutoffs during 2014-2018, which is controlled by ρ . Solid line and dashed line in both figures represent simulated moments and data, respectively. For simulated moments, we simulate each applicant's choices 50 times and take the average over the whole relevant sample. Hollow circles in orange represent the simulated moments where no noise is added ($\sigma = 0$). Hollow triangles in brown represent the simulated moment where small scale noise is added ($\sigma = 0.1$). Plus signs in green represent the simulated moments where substantial noise is added ($\sigma = 1$). This graph is helpful for the discussion in Section 4.4.

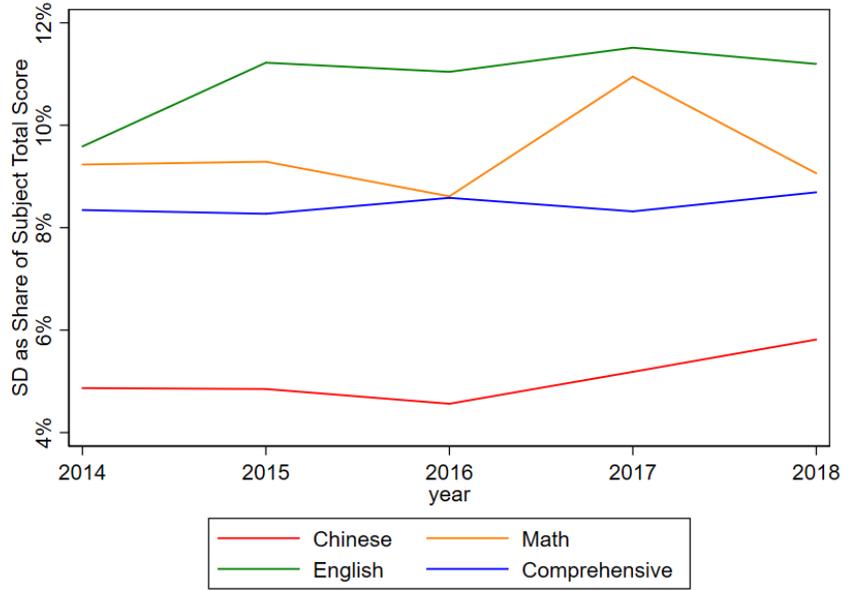
Figure A6: Example of Change in Priority Score Leading to Change in Ratio of Assignment Probability



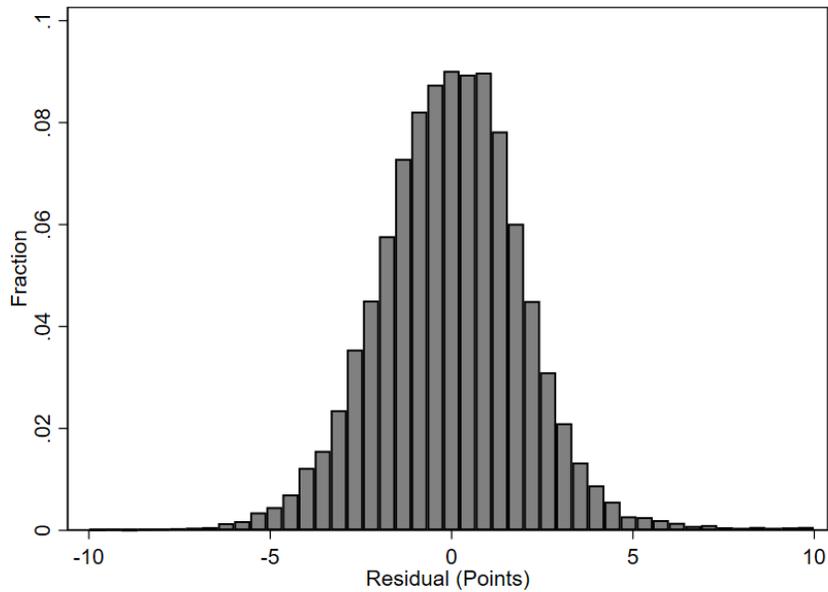
Note: This figure plots an example of the cumulative distributions of the cutoffs for two colleges, A1 and B1. Both distributions are normal distribution with standard deviation of 5, and the mean being 600 and 605 respectively. As shown in the upper horizontal axis, changes in priority scores lead to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

Figure A7: Impact of Subject Difficulty Variation on Admission Probability

(a) Difficulty of Subjects Varies Across Years

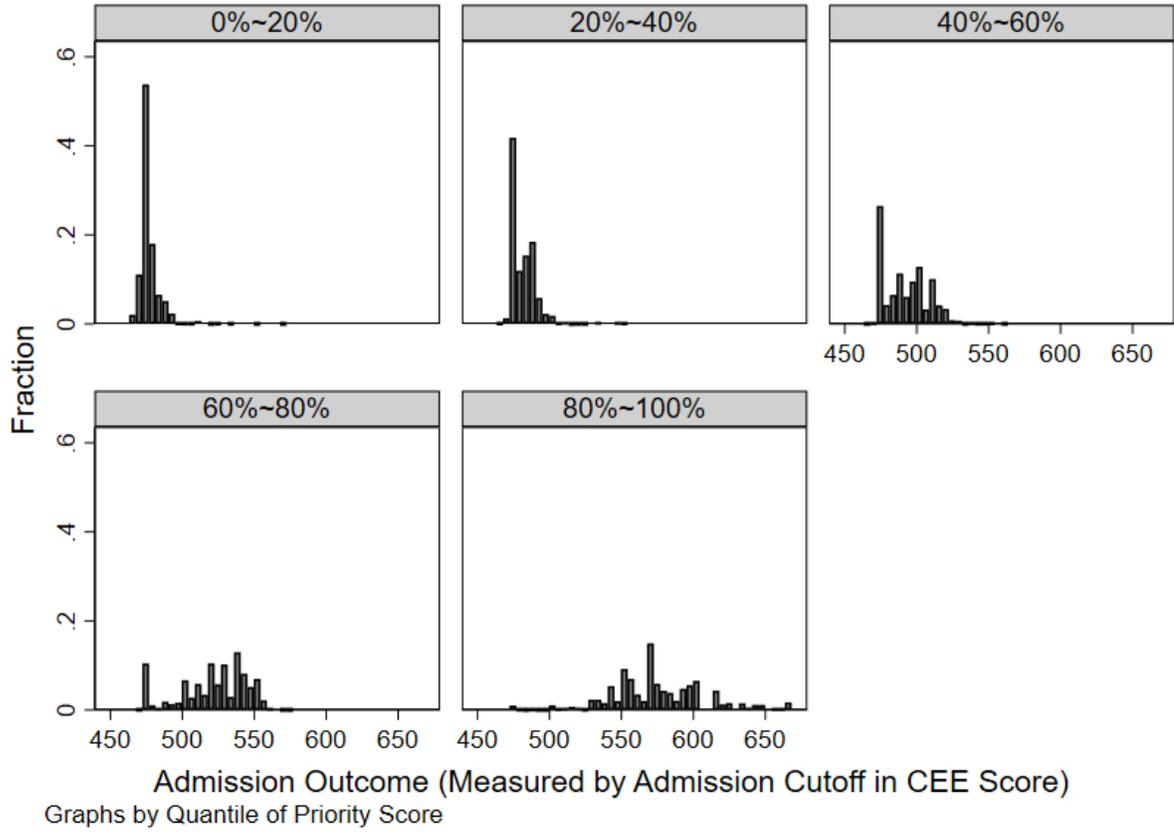


(b) Magnitude of Shock to Admission Probability is Sizable



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.

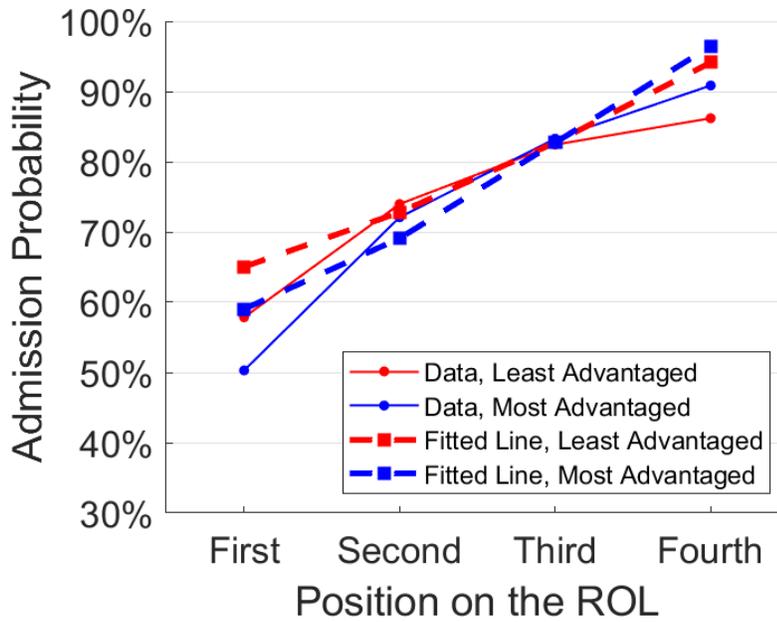
Figure A8: Competitiveness of Admitting College: by CEE Score Quantile



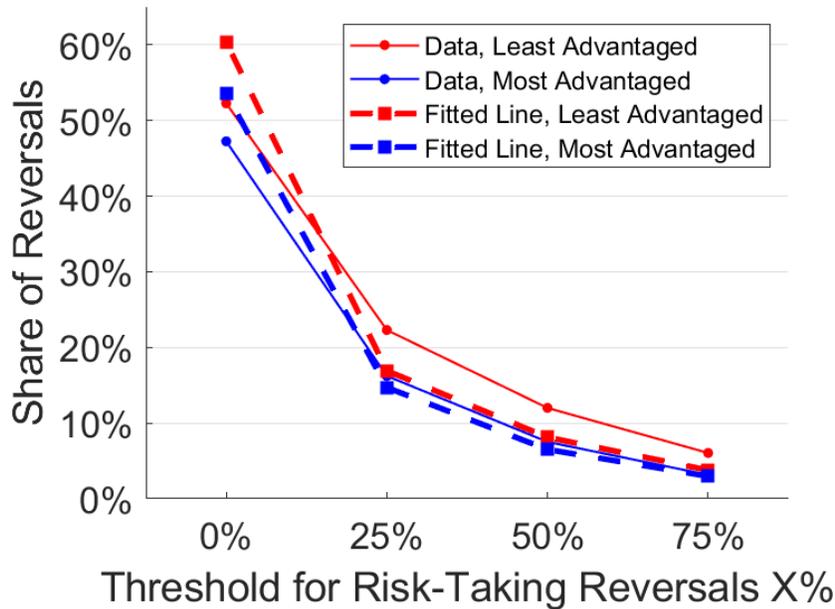
Note: This figure plots the distribution of colleges that admit students during 2014-2018. We split the entire sample of STEM applicants into five groups according to their CEE Score, with the first quintile being the group with lowest CEE Score and the fifth being the highest. This graph is helpful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

Figure A9: Data & Fit of Mixture Model: Advantaged vs. Disadvantaged

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



(b) Data vs. Fit: Share of Risk-Taking 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.⁶⁸ Subfigure (b) plots the share of risk-taking reversals with different levels of threshold X%.

B Supplementary Tables

Table B1: Examples of Admission Rules

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ex. Number	Priority Score	Admission Cutoffs				Admission Outcome
		A	B	C	D	
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 2.3.

Table B2: Validity of Estimates of Unconditional Probability

	(1)	(2)	(3)	(4)
	Admitted to First		Admitted to Second	
Estimated Uncond. Prob. to First	1.0015*** (0.0043)	1.0117*** (0.0081)		
Estimated Uncond. Prob. to Second			0.9883*** (0.0060)	1.0252*** (0.0107)
Constant	-0.0043* (0.0024)	-0.0050 (0.0040)	0.0033 (0.0037)	-0.0094 (0.0060)
Subsample (Science/Humanity)	Science	Humanity	Science	Humanity
Share of Admitted	.41	.314	.481	.419
Predicted Share of Admitted	.413	.316	.484	.418
F-Test: $\alpha = 0, \beta = 1$.074	.328	.085	.059
Number of Observations	36104	8230	20929	5571
R squared	0.605	0.652	0.566	0.624

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*** (0.0082)	-0.1061*** (0.0126)	-0.0962*** (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* (0.0125)	-0.0106 (0.0142)	0.0001 (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 4.4.

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%

Question #	Panel A2: MPL for Question Group 1		Panel C2: MPL for Question Group 3	
	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%

Question #	Panel B: MPL for Question Series 2	
	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: Subjective Beliefs

	(1)	(2)	(3)	(4)
	Belief-Est.	Prob.	Belief-Est.	Prob.
SES Index (Normalized)	1.20%** (0.51%)	2.17%*** (0.62%)	1.05%*** (0.35%)	0.93%** (0.43%)
Mean		11.3%		30.6%
Priority Score	Yes	Yes	Yes	Yes
Demographic Variables	No	Yes	No	Yes
College Preferences	No	Yes	No	Yes
Number of Observations	5341	5341	5341	5341
R squared	0.117	0.155	0.057	0.112

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 8.1.

Table B6: Full Set of Parameter Estimates for Benchmark Model

Sample (Quantile of Priority Score) Model	(1) 40%-60%		(3) 60%-80%		(5) 80%-100%	
	Rational	Mixture	Rational	Mixture	Rational	Mixture
γ_0		0.1252 [0.0105]		-0.1973 [0.011]		0.208 [0.0148]
γ_1		-0.1498 [0.0105]		-0.1493 [0.0121]		-0.247 [0.0159]
O^{RN}	201.2587 [11.9669]	187.4907 [33.1842]	111.921 [8.5226]	176.7342 [32.3841]	195.5955 [16.8046]	8.7853 [2.2729]
O^{DC}		78.7562 [29.3449]		-34.3799 [1.9681]		44.9209 [78.0733]
μ_C^{RN}	-0.0435 [0.0066]	-0.375 [0.0355]	0.4131 [0.0216]	-0.3652 [0.0241]	0.3066 [0.014]	-0.3359 [0.0266]
ν_C^{RN}	-0.0776 [0.0053]	0.0284 [0.0095]	-0.1018 [0.0107]	-0.0357 [0.0105]	-0.1067 [0.0092]	0.0066 [0.0086]
$\ln(\sigma_C^{RN})$	-4.1131 [0.4797]	-1.062 [0.0968]	-0.5165 [0.039]	-1.992 [0.1842]	-4.3937 [0.7947]	-4.9764 [2.121]
μ_C^{DC}		-0.4856 [0.0488]		-0.4591 [0.0268]		-0.4782 [0.024]
ν_C^{DC}		0.3762 [0.0505]		-0.0812 [0.0112]		-0.0187 [0.0088]
$\ln(\sigma_C^{DC})$		0.448 [0.0526]		-2.0757 [0.2075]		-3.3633 [0.5757]
μ_{d2}^{RN}	-6.8873 [0.2233]	-9.992 [0.5761]	-4.3441 [0.1344]	0.1874 [0.1141]	-3.6878 [0.0849]	-4.9847 [0.4778]
ν_{d2}^{RN}	2.2877 [0.0969]	-0.5175 [0.2054]	-0.0243 [0.008]	0.1652 [0.0751]	1.9706 [0.0751]	1.1632 [0.1969]
$\ln(\sigma_{d2}^{RN})$	1.9632 [0.0301]	0.6009 [0.2898]	0.2952 [0.0362]	-0.8687 [0.5457]	-2.4492 [0.5543]	1.5638 [0.1205]
μ_{d2}^{DC}		-0.8002 [0.1989]		1.0772 [0.0987]		2.0291 [0.1602]
ν_{d2}^{DC}		1.3624 [0.2314]		1.0953 [0.12]		0.9078 [0.1419]
$\ln(\sigma_{d2}^{DC})$		1.953 [0.0981]		1.5628 [0.0886]		1.3889 [0.1126]
$\ln(\sigma_\epsilon)$	-0.1207 [0.0255]	2.6702 [0.0821]	-0.9946 [0.1145]	2.4079 [0.0821]	-0.9616 [0.0898]	-0.8188 [0.5159]
μ_{d1}	19.2221 [0.8053]	11.789 [0.9965]	19.7298 [0.6462]	-6.0303 [0.4852]	19.2848 [0.4567]	-0.3039 [0.1945]
$\mu^{X,STEM}$	2.5861 [0.1941]	0.2433 [0.1266]	-1.0096 [0.2548]	0.9482 [0.3918]	-3.2708 [0.8692]	-0.6504 [0.2704]
$\mu^{X,FIN}$	-2.5268 [0.578]	-1.4682 [0.9938]	-0.8048 [0.1611]	0.3164 [0.3252]	-17.6289 [2.0334]	-1.6289 [0.6835]
$\mu^{X,MED}$	-1.2038 [0.2107]	2.9692 [0.7749]	-1.9315 [0.3601]	-1.2749 [0.4728]	-11.0285 [2.1469]	-19.0556 [3.4944]
ν_{d1}	2.7649 [0.0326]	0.9637 [0.263]	0.8853 [0.1257]	1.5536 [0.1478]	1.3512 [0.0678]	2.8387 [0.0951]
$\nu^{X,STEM}$	1.5886 [0.1374]	2.9866 [0.147]	2.9986 [0.1814]	2.9974 [0.1647]	2.8672 [0.1904]	1.9145 [0.1866]
$\nu^{X,FIN}$	2.3696 [0.0645]	2.8947 [0.1176]	0.3958 [0.1496]	2.0263 [0.1408]	2.8453 [0.1074]	2.4398 [0.1169]
$\nu^{X,MED}$	1.6335 [0.0656]	-1.4377 [1.6394]	1.4208 [0.1203]	0.1856 [0.3431]	2.2924 [0.1711]	2.8106 [0.2065]
$\ln(\sigma_{d1})$	-3.1846 [0.3308]	9.1148 [0.9704]	2.7593 [0.0745]	1.4381 [0.3302]	-9.4213 [0.407]	1.1769 [0.4923]
$\ln(\sigma^{X,STEM})$	0.8442 [0.1108]	2.7324 [0.3584]	1.3985 [0.2833]	0.9126 [0.3609]	-1.5138 [0.2493]	-1.478 [0.3231]
$\ln(\sigma^{X,FIN})$	1.4157 [0.2093]	1.5411 [0.7664]	-0.1749 [0.0362]	-1.1974 [0.329]	0.0788 [0.0437]	-0.8185 [0.4208]
$\ln(\sigma^{X,MED})$	-1.4415 [0.164]	-1.0368 [0.5986]	-0.8789 [0.1118]	-3.426 [0.5875]	-2.1369 [0.3572]	-6.5154 [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 5, 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 B7: Full Set of Parameter Estimates for Model with Subjective Beliefs

Sample (Quantile of Priority Score) Model	(1) 40%-60%		(3) 60%-80%		(5) 80%-100%	
	Rational	Mixture	Rational	Mixture	Rational	Mixture
γ_0		2.8421		3.2691		3.8864
γ_1		[0.0968]		[0.0704]		[0.0962]
O^{RN}		0.9663		-0.2743		-0.4509
O^{DC}		[0.0692]		[0.0798]		[0.144]
μ_C^{RN}	47.6584	107.0377	186.5335	10.6943	180.4882	137.3104
μ_C^{DC}	[1.21]	[43.6744]	[37.5617]	[8.8221]	[18.1934]	[117.3933]
ν_C^{RN}		157.7041		190.9884		183.2862
ν_C^{DC}		[13.5568]		[26.0062]		[10.4437]
$\ln(\sigma_C^{RN})$	-0.318	0.125	-0.0999	4.5286	0.0903	10.4447
$\ln(\sigma_C^{DC})$	[0.0157]	[0.0452]	[0.0105]	[1.1712]	[0.0051]	[9.1129]
μ_{d2}^{RN}	-0.3331	0.5939	0.0333	-2.0243	-0.0811	-2.6561
μ_{d2}^{DC}	[0.0165]	[0.0534]	[0.0023]	[0.7408]	[0.0032]	[5.2059]
ν_{d2}^{RN}	0.5627	-1.4185	-4.9141	-2.9601	-4.5224	0.969
ν_{d2}^{DC}	[0.0189]	[0.2319]	[0.4723]	[3.0393]	[0.2442]	[1.7258]
$\ln(\sigma_{d2}^{RN})$		-0.4938		-0.4782		-0.4313
$\ln(\sigma_{d2}^{DC})$		[0.0217]		[0.0173]		[0.0113]
μ_{d1}^{RN}		0.1451		0.0125		0.0859
μ_{d1}^{DC}		[0.0091]		[0.0048]		[0.0055]
ν_{d1}^{RN}		-1.4356		-1.7559		-2.4135
ν_{d1}^{DC}		[0.0855]		[0.0767]		[0.1239]
$\ln(\sigma_{d1}^{RN})$	-7.5468	-9.9297	-3.735	-2.4629	0.3301	-9.605
$\ln(\sigma_{d1}^{DC})$	[0.1596]	[1.2335]	[0.1393]	[0.5696]	[0.0176]	[3.4907]
μ_{d1}^{RN}	3.5104	9.9625	-0.0764	0.4132	2.8769	-7.116
μ_{d1}^{DC}	[0.0665]	[2.1119]	[0.0202]	[0.2359]	[0.0509]	[5.0562]
ν_{d1}^{RN}	1.5154	1.4246	-1.7818	-0.8556	-0.1169	-3.3158
ν_{d1}^{DC}	[0.0456]	[0.3211]	[0.3147]	[0.9039]	[0.0103]	[8.6852]
$\ln(\sigma_{d1}^{RN})$		-3.2083		-2.1032		-1.5258
$\ln(\sigma_{d1}^{DC})$		[0.144]		[0.117]		[0.0829]
μ_{d1}^{RN}		-0.3515		1.0558		-2.7604
μ_{d1}^{DC}		[0.1002]		[0.1114]		[0.1335]
ν_{d1}^{RN}		1.8952		1.9454		1.8639
ν_{d1}^{DC}		[0.0427]		[0.0518]		[0.0384]
$\ln(\sigma_{d1}^{RN})$	2.9464	-0.5798	1.8222	-0.0608	1.4472	-0.6756
$\ln(\sigma_{d1}^{DC})$	[0.0307]	[0.2055]	[0.0397]	[0.0425]	[0.0283]	[0.2144]
μ_{d1}^{RN}	18.7384	3.1024	16.9153	-0.3039	-2.2612	2.2743
μ_{d1}^{DC}	[0.5076]	[0.4419]	[0.691]	[0.1461]	[0.0893]	[0.3412]
ν_{d1}^{RN}	-5.1322	3.8767	2.0138	7.4614	8.0496	2.8957
ν_{d1}^{DC}	[0.3121]	[0.3017]	[0.0961]	[0.453]	[0.3364]	[0.1916]
$\ln(\sigma_{d1}^{RN})$	-11.7332	-2.9445	-1.4988	0.6211	-3.7295	5.735
$\ln(\sigma_{d1}^{DC})$	[0.8499]	[0.5674]	[0.3792]	[0.381]	[0.4408]	[0.3263]
μ_{d1}^{RN}	7.1795	-1.0502	1.918	-1.6456	-7.5212	-14.348
μ_{d1}^{DC}	[0.5578]	[0.2793]	[0.1722]	[0.3956]	[0.6757]	[1.2808]
ν_{d1}^{RN}	0.4596	-0.0773	2.7294	0.0399	0.5844	2.2082
ν_{d1}^{DC}	[0.073]	[0.0459]	[0.0269]	[0.0444]	[0.0516]	[0.1145]
$\ln(\sigma_{d1}^{RN})$	2.7988	2.9991	1.752	2.9994	2.9885	-2.9022
$\ln(\sigma_{d1}^{DC})$	[0.1119]	[0.1172]	[0.1591]	[0.1179]	[0.0706]	[1.7772]
μ_{d1}^{RN}	2.8043	2.65	1.5981	2.8016	2.9536	-2.1044
μ_{d1}^{DC}	[0.0681]	[0.0686]	[0.1113]	[0.0577]	[0.0369]	[1.4557]
ν_{d1}^{RN}	-0.6704	1.2725	-1.6872	1.7481	1.0976	2.4194
ν_{d1}^{DC}	[0.3478]	[0.1653]	[0.9522]	[0.1583]	[0.1879]	[0.1209]
$\ln(\sigma_{d1}^{RN})$	-8.0958	6.2332	4.8218	2.5848	-14.3383	19.9639
$\ln(\sigma_{d1}^{DC})$	[0.2669]	[0.4444]	[0.1587]	[0.5162]	[0.2752]	[0.6979]
μ_{d1}^{RN}	-0.3587	-1.2404	0.4852	1.9126	5.6399	-3.3723
μ_{d1}^{DC}	[0.1268]	[0.2316]	[0.0968]	[0.2988]	[0.2929]	[0.2044]
ν_{d1}^{RN}	-2.7558	-4.93	-1.3575	-1.1153	7.3209	-5.1778
ν_{d1}^{DC}	[0.4987]	[0.4187]	[0.1484]	[0.3136]	[0.2506]	[0.3016]
$\ln(\sigma_{d1}^{RN})$	-7.01	-3.1224	-1.259	-2.8703	-6.5766	-9.2358
$\ln(\sigma_{d1}^{DC})$	[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 6, 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 B8: Major Preferences and Its Impact on Risk Taking

	(1)	(2)	(3)	(4)	(5)	(6)
	Major Top Concern	Major Top Concern	Estimated Prob	Estimated Prob	Subjective Beliefs	Subjective Beliefs
SES Index (Normalized)	-2.24%** (0.92%)	-2.66%** (1.17%)				
Major Top Concern			3.25% (2.85%)	4.09% (3.00%)	8.94%*** (2.43%)	8.01%*** (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 8.3.

Table B9: 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% (1.07%)	49.56% (1.32%)	54.96% (1.21%)	45.56% (1.31%)
Mean Assignment Probability of 2nd Choice	64.96% (0.98%)	70.22% (1.18%)	74.05% (1.02%)	67.54% (1.18%)
Mean Assignment Probability of 3rd Choice	77.15% (0.88%)	81.92% (0.99%)	83.22% (0.87%)	79.63% (1.02%)
Mean Assignment Probability of 4th Choice	87.73% (0.7%)	89.83% (0.81%)	92.26% (0.64%)	91.82% (0.72%)
Share of Reversals $R \geq 75\%$	13.85% (0.91%)	9.22% (0.98%)	7.53% (0.83%)	6.88% (0.87%)
Share of Reversals $R \geq 50\%$	20.63% (1.07%)	15.41% (1.22%)	13.5% (1.08%)	15.5% (1.25%)
Share of Reversals $R \geq 25\%$	31.73% (1.23%)	25.42% (1.48%)	23.97% (1.35%)	26.92% (1.53%)
Share of Reversals $R \geq 0\%$	60.8% (1.29%)	56.36% (1.68%)	54.89% (1.57%)	55.36% (1.72%)
Competitiveness(Normalized) of Admitting College Mean	0.384 (0.0077)	0.3678 (0.0099)	0.3876 (0.0095)	0.3632 (0.0105)
Share of Admission	96.02% (0.52%)	96.06% (0.66%)	97.55% (0.49%)	97.79% (0.51%)
Competitiveness(Normalized) Mean: First Choices	-0.107 (0.0142)	-0.1442 (0.0165)	-0.2118 (0.0149)	-0.0746 (0.0171)
Distance(Normalized) Mean: First Choices	-0.8255 (0.0098)	-0.5104 (0.0118)	-0.4462 (0.0111)	-0.0974 (0.014)
STEM Concentration Share: First Choices	39.82% (0.8%)	44.21% (1.09%)	44.03% (1.09%)	48.37% (1.14%)
Finance Concentration Share: First Choices	7.4% (0.4%)	8.66% (0.74%)	7.05% (0.75%)	6.99% (1.06%)
Medical School Share: First Choices	18.3% (0.7%)	14.17% (1.12%)	14.09% (1.06%)	10.96% (1.23%)
Competitiveness(Normalized) Mean: Second Choices	-0.2998 (0.0126)	-0.3635 (0.0151)	-0.4059 (0.013)	-0.3054 (0.0143)
Distance(Normalized) Mean: Second Choices	-0.6479 (0.0084)	-0.5372 (0.01)	-0.4028 (0.01)	-0.0053 (0.0129)
STEM Concentration Share: Second Choices	45.01% (0.85%)	45.14% (1.07%)	49.16% (1.11%)	50.23% (1.15%)
Finance Concentration Share: Second Choices	8.1% (0.52%)	10.52% (0.78%)	6.52% (0.64%)	9.04% (1.03%)
Medical School Share: Second Choices	11.84% (0.83%)	10.86% (1.12%)	11.85% (1.15%)	7.75% (1.29%)
Competitiveness(Normalized) Mean: Third Choices	-0.456 (0.0123)	-0.5116 (0.0133)	-0.5213 (0.0122)	-0.4475 (0.0134)
Distance(Normalized) Mean: Third Choices	-0.7354 (0.0082)	-0.538 (0.0096)	-0.3114 (0.0086)	-0.0846 (0.0116)
STEM Concentration Share: Third Choices	45.34% (0.82%)	48.08% (1.18%)	47.67% (1.13%)	51.43% (1.17%)
Finance Concentration Share: Third Choices	8.39% (0.42%)	8.15% (0.7%)	7.09% (0.65%)	8.71% (0.97%)
Medical School Share: Third Choices	10.95% (0.81%)	8.96% (1.14%)	8.5% (1.2%)	6.32% (1.33%)
Competitiveness(Normalized) Mean: Fourth Choices	-0.6332 (0.0113)	-0.6766 (0.0129)	-0.706 (0.0108)	-0.6726 (0.0122)
Distance(Normalized) Mean: Fourth Choices	-1.0074 (0.0068)	-0.7478 (0.008)	-0.5377 (0.0081)	-0.3027 (0.0104)
STEM Concentration Share: Fourth Choices	38.89% (0.83%)	39.76% (1.05%)	42.89% (1.03%)	45.34% (1.1%)
Finance Concentration Share: Fourth Choices	4.43% (0.43%)	5.51% (0.57%)	5.52% (0.6%)	4.35% (0.85%)
Medical School Share: Fourth Choices	12.16% (0.73%)	9.34% (1.05%)	7.43% (1.06%)	8.1% (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 B10: Fit of Benchmark Rational Model: 40 - 60 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	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 $R_{\geq 75\%}$	8.21%	7.56%	7.6%	8.3%
	[-5.63%]	[-1.66%]	[0.07%]	[1.42%]
Share of Reversals $R_{\geq i=50\%}$	11.06%	10.29%	10.22%	10.32%
	[-9.57%]	[-5.12%]	[-3.28%]	[-5.18%]
Share of Reversals $R_{\geq 25\%}$	14.93%	13.58%	13.06%	12.51%
	[-16.8%]	[-11.84%]	[-10.91%]	[-14.41%]
Share of Reversals $R_{\geq 0\%}$	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 5. 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 B11: Fit of Benchmark Mixture Model: 40 - 60 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	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 $R \geq 75\%$	4.16%	3.52%	3.14%	3.42%
	[-9.68%]	[-5.7%]	[-4.39%]	[-3.46%]
Share of Reversals $R \geq 50\%$	6.98%	6.5%	6.23%	6.75%
	[-13.65%]	[-8.91%]	[-7.28%]	[-8.76%]
Share of Reversals $R \geq 25\%$	14.36%	14.07%	13.93%	14.09%
	[-17.38%]	[-11.35%]	[-10.05%]	[-12.83%]
Share of Reversals $R \geq 0\%$	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 5. 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 B12: Value of Moments: 60 - 80 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	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 $R \geq 75\%$	5.99%	2.93%	3.15%	2.63%
	(0.67%)	(0.6%)	(0.56%)	(0.49%)
Share of Reversals $R \geq 50\%$	14.5%	8.91%	7.93%	7.34%
	(1%)	(1.01%)	(0.87%)	(0.79%)
Share of Reversals $R \geq 25\%$	27.27%	18.93%	18.31%	17.48%
	(1.26%)	(1.38%)	(1.25%)	(1.15%)
Share of Reversals $R \geq 0\%$	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 B13: 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 $R \geq 75\%$	3.43%	2.89%	2.63%	2.02%
	[-2.56%]	[-0.04%]	[-0.52%]	[-0.61%]
Share of Reversals $R \geq 50\%$	7.9%	6.55%	6.1%	4.97%
	[-6.6%]	[-2.36%]	[-1.84%]	[-2.37%]
Share of Reversals $\geq 25\%$	15.22%	12.92%	11.79%	9.84%
	[-12.04%]	[-6.01%]	[-6.52%]	[-7.64%]
Share of Reversals $R \geq 0\%$	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 5. 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 B14: Fit of Benchmark Mixture Model: 60 - 80 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	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 $R \geq 75\%$	4.13%	2.46%	1.75%	0.81%
	[-1.86%]	[-0.47%]	[-1.41%]	[-1.82%]
Share of Reversals $R \geq 50\%$	11.9%	8.65%	6.75%	4.27%
	[-2.6%]	[-0.26%]	[-1.19%]	[-3.06%]
Share of Reversals $R \geq 25\%$	28.79%	24.93%	22.07%	17.78%
	[1.52%]	[6.01%]	[3.76%]	[0.3%]
Share of Reversals $R \geq 0\%$	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 5. 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 B15: 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% (1.23%)	61.76% (1.38%)	62.19% (1.15%)	55.77% (0.82%)
Mean Assignment Probability of 2nd Choice	81.55% (0.88%)	82.78% (0.91%)	83.32% (0.76%)	78.51% (0.58%)
Mean Assignment Probability of 3rd Choice	90.19% (0.65%)	90.63% (0.71%)	91.4% (0.53%)	89.97% (0.39%)
Mean Assignment Probability of 4th Choice	95.1% (0.51%)	96.38% (0.44%)	96.99% (0.31%)	96.59% (0.24%)
Share of Reversals $R \geq 75\%$	2.82% (0.58%)	2.13% (0.57%)	1.47% (0.41%)	1.69% (0.3%)
Share of Reversals $R \geq 50\%$	6.98% (0.9%)	4.56% (0.82%)	3.06% (0.59%)	3.83% (0.45%)
Share of Reversals $R \geq 25\%$	16.28% (1.31%)	10.03% (1.18%)	10.32% (1.04%)	10.33% (0.72%)
Share of Reversals $R \geq 0\%$	49.33% (1.77%)	44.38% (1.96%)	43.99% (1.69%)	40.57% (1.16%)
Competitiveness(Normalized) of Admitting College Mean	0.423 (0.0185)	0.3781 (0.0168)	0.3492 (0.0135)	0.307 (0.0094)
Share of Admission	98.41% (0.44%)	98.78% (0.43%)	99.32% (0.28%)	99.73% (0.12%)
Competitiveness(Normalized) Mean: First Choices	1.3059 (0.0228)	1.3551 (0.0266)	1.4226 (0.024)	1.6837 (0.0167)
Distance(Normalized) Mean: First Choices	-0.341 (0.0163)	-0.3134 (0.018)	-0.1472 (0.0158)	0.0324 (0.0116)
STEM Concentration Share: First Choices	38.8% (1.18%)	38.91% (1.22%)	34.81% (0.96%)	32.97% (0.57%)
Finance Concentration Share: First Choices	9.18% (0.55%)	9.73% (0.72%)	9.86% (0.76%)	9.57% (0.58%)
Medical School Share: First Choices	10.04% (1.08%)	9.57% (1.24%)	7.14% (1.17%)	4.7% (0.85%)
Competitiveness(Normalized) Mean: Second Choices	1.0676 (0.0207)	1.1332 (0.0229)	1.1852 (0.0227)	1.4278 (0.015)
Distance(Normalized) Mean: Second Choices	-0.3268 (0.0158)	-0.1971 (0.0181)	-0.0907 (0.0154)	0.043 (0.0112)
STEM Concentration Share: Second Choices	42.18% (1.15%)	39.45% (1.07%)	42.3% (1.03%)	35.26% (0.62%)
Finance Concentration Share: Second Choices	8.93% (0.6%)	11.86% (0.65%)	8.97% (0.75%)	8.23% (0.58%)
Medical School Share: Second Choices	9.18% (1.13%)	8.63% (1.39%)	5.63% (1.19%)	3.52% (0.87%)
Competitiveness(Normalized) Mean: Third Choices	0.9189 (0.0212)	0.9631 (0.0243)	1.0387 (0.0224)	1.2415 (0.0148)
Distance(Normalized) Mean: Third Choices	-0.3 (0.016)	-0.199 (0.0176)	-0.0996 (0.0155)	0.033 (0.011)
STEM Concentration Share: Third Choices	41.88% (1.17%)	47.13% (1.18%)	42.28% (1.03%)	37.49% (0.71%)
Finance Concentration Share: Third Choices	9% (0.65%)	9.77% (0.77%)	8.99% (0.72%)	9.04% (0.57%)
Medical School Share: Third Choices	9.38% (1.08%)	6.67% (1.36%)	5.76% (1.22%)	3.92% (0.91%)
Competitiveness(Normalized) Mean: Fourth Choices	0.6635 (0.0234)	0.6843 (0.0265)	0.7838 (0.0241)	0.981 (0.0161)
Distance(Normalized) Mean: Fourth Choices	-0.4375 (0.0156)	-0.3218 (0.0172)	-0.1766 (0.0148)	0.012 (0.0109)
STEM Concentration Share: Fourth Choices	41.21% (1.1%)	42.41% (1.26%)	40.52% (0.91%)	38.38% (0.67%)
Finance Concentration Share: Fourth Choices	8.47% (0.64%)	10.92% (0.67%)	10.37% (0.79%)	7.34% (0.56%)
Medical School Share: Fourth Choices	11.17% (1.14%)	9.34% (1.36%)	7.42% (1.22%)	5.78% (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 B16: Fit of Benchmark Rational Model: 80 - 100 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	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 $R \geq 75\%$	4.76%	3.52%	3.41%	3.32%
	[1.94%]	[1.4%]	[1.94%]	[1.62%]
Share of Reversals $R \geq 50\%$	7.67%	5.75%	5.83%	6.28%
	[0.69%]	[1.19%]	[2.77%]	[2.45%]
Share of Reversals $R \geq 25\%$	15.07%	12.56%	13.29%	13.28%
	[-1.21%]	[2.53%]	[2.98%]	[2.94%]
Share of Reversals $R \geq 0\%$	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 5. 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 B17: 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%	67.9%	66.06%	63.71%
	[8.61%]	[6.14%]	[3.87%]	[7.94%]
Mean Assignment Probability of 2nd Choice	81.36%	79.25%	77.4%	75.03%
	[-0.19%]	[-3.53%]	[-5.92%]	[-3.48%]
Mean Assignment Probability of 3rd Choice	89.09%	87.94%	87.42%	86.78%
	[-1.1%]	[-2.69%]	[-3.98%]	[-3.19%]
Mean Assignment Probability of 4th Choice	97.29%	97.4%	97.38%	97.49%
	[2.19%]	[1.02%]	[0.39%]	[0.9%]
Share of Reversals $R_{\geq 75\%}$	2.45%	2.85%	2.94%	4.04%
	[-0.37%]	[0.72%]	[1.47%]	[2.35%]
Share of Reversals $R_{\geq 50\%}$	5.61%	6.26%	6.45%	7.7%
	[-1.37%]	[1.71%]	[3.39%]	[3.87%]
Share of Reversals $R_{\geq 25\%}$	9.91%	11.06%	11.81%	13.04%
	[-6.37%]	[1.03%]	[1.49%]	[2.7%]
Share of Reversals $R_{\geq 0\%}$	58.84%	57.06%	56.02%	53.96%
	[9.52%]	[12.69%]	[12.03%]	[13.39%]
Competitiveness(Normalized) of Admitting College Mean	0.525	0.505	0.4894	0.4717
	[0.102]	[0.1269]	[0.1402]	[0.1647]
Share of Admission	99.72%	99.72%	99.68%	99.69%
	[1.31%]	[0.93%]	[0.37%]	[-0.04%]
Competitiveness(Normalized) Mean: First Choices	1.2309	1.2911	1.3683	1.5698
	[-0.0749]	[-0.064]	[-0.0544]	[-0.1139]
Distance(Normalized) Mean: First Choices	-0.3479	-0.2025	-0.1318	0.0557
	[-0.0069]	[0.1109]	[0.0154]	[0.0233]
STEM Concentration Share: First Choices	42.54%	41.04%	40.14%	37.48%
	[3.74%]	[2.14%]	[5.34%]	[4.52%]
Finance Concentration Share: First Choices	9.27%	9.64%	9.61%	8.96%
	[0.09%]	[-0.09%]	[-0.25%]	[-0.6%]
Medical School Share: First Choices	10.02%	6.67%	4.73%	2.13%
	[-0.02%]	[-2.9%]	[-2.41%]	[-2.57%]
Competitiveness(Normalized) Mean: Second Choices	1.0832	1.1446	1.2309	1.4415
	[0.0156]	[0.0114]	[0.0457]	[0.0136]
Distance(Normalized) Mean: Second Choices	-0.2974	-0.1577	-0.0871	0.094
	[0.0293]	[0.0394]	[0.0036]	[0.051]
STEM Concentration Share: Second Choices	45.64%	44.3%	43.11%	38.2%
	[3.46%]	[4.86%]	[0.81%]	[2.94%]
Finance Concentration Share: Second Choices	10.05%	10.49%	10.14%	9.46%
	[1.12%]	[-1.38%]	[1.17%]	[1.23%]
Medical School Share: Second Choices	9.66%	6.81%	5.19%	2.99%
	[0.48%]	[-1.82%]	[-0.44%]	[-0.53%]
Competitiveness(Normalized) Mean: Third Choices	0.9598	1.0195	1.1032	1.3041
	[0.0409]	[0.0564]	[0.0645]	[0.0626]
Distance(Normalized) Mean: Third Choices	-0.3201	-0.1863	-0.1141	0.0592
	[-0.0201]	[0.0127]	[-0.0145]	[0.0263]
STEM Concentration Share: Third Choices	41.78%	40.58%	40.44%	38.39%
	[-0.1%]	[-6.55%]	[-1.84%]	[0.91%]
Finance Concentration Share: Third Choices	9.5%	9.4%	9.25%	9.34%
	[0.5%]	[-0.37%]	[0.27%]	[0.29%]
Medical School Share: Third Choices	9.06%	6.73%	5.23%	3.36%
	[-0.32%]	[0.06%]	[-0.53%]	[-0.56%]
Competitiveness(Normalized) Mean: Fourth Choices	0.7293	0.7723	0.8496	1.0278
	[0.0657]	[0.088]	[0.0657]	[0.0468]
Distance(Normalized) Mean: Fourth Choices	-0.4108	-0.2956	-0.2228	-0.0546
	[0.0267]	[0.0262]	[-0.0462]	[-0.0666]
STEM Concentration Share: Fourth Choices	37.27%	36.38%	35.72%	34.33%
	[-3.94%]	[-6.03%]	[-4.79%]	[-4.06%]
Finance Concentration Share: Fourth Choices	9.2%	9.76%	9.95%	10.37%
	[0.73%]	[-1.15%]	[-0.42%]	[3.03%]
Medical School Share: Fourth Choices	11.82%	8.78%	7.33%	4.36%
	[0.65%]	[-0.55%]	[-0.09%]	[-1.42%]

Note: This table presents details of the fit of mixture model in Section 7.4 and Table 5. 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 B18: Fit of Benchmark Rational Model with Subjective Beliefs: 40 - 60 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	13.6%	12.67%	12.12%	13.02%
	[-34.95%]	[-36.89%]	[-42.84%]	[-32.53%]
Mean Assignment Probability of 2nd Choice	22.84%	21.32%	20.62%	21.87%
	[-42.12%]	[-48.89%]	[-53.43%]	[-45.68%]
Mean Assignment Probability of 3rd Choice	36.22%	33.91%	33.24%	35.13%
	[-40.94%]	[-48.01%]	[-49.98%]	[-44.5%]
Mean Assignment Probability of 4th Choice	83.72%	80.52%	78.9%	80.08%
	[-4.01%]	[-9.31%]	[-13.36%]	[-11.74%]
Share of Reversals $R \geq 75\%$	6.77%	5.51%	5.36%	9.48%
	[-7.07%]	[-3.72%]	[-2.17%]	[2.6%]
Share of Reversals $R \geq 50\%$	15.06%	13.44%	12.39%	15.36%
	[-5.58%]	[-1.97%]	[-1.11%]	[-0.14%]
Share of Reversals $R \geq 25\%$	28.43%	27.15%	25.29%	25.51%
	[-3.3%]	[1.73%]	[1.32%]	[-1.42%]
Share of Reversals $R \geq 0\%$	57.83%	58.19%	57.96%	55.79%
	[-2.96%]	[1.84%]	[3.07%]	[0.43%]
Competitiveness(Normalized) of Admitting College Mean	0.346	0.3204	0.3205	0.3824
	[-0.038]	[-0.0474]	[-0.0672]	[0.0192]
Share of Admission	90.84%	88.47%	87.32%	87.75%
	[-5.18%]	[-7.59%]	[-10.23%]	[-10.04%]
Competitiveness(Normalized) Mean: First Choices	0.4613	0.4063	0.4126	0.5303
	[0.5683]	[0.5505]	[0.6244]	[0.6049]
Distance(Normalized) Mean: First Choices	-0.6981	-0.5849	-0.455	-0.0587
	[0.1274]	[-0.0744]	[-0.0087]	[0.0388]
STEM Concentration Share: First Choices	40.72%	45.58%	48.16%	50.08%
	[0.9%]	[1.37%]	[4.13%]	[1.71%]
Finance Concentration Share: First Choices	7.37%	8.74%	9.26%	8.44%
	[-0.03%]	[0.07%]	[2.21%]	[1.44%]
Medical School Share: First Choices	19.6%	14.36%	12.59%	10.24%
	[1.3%]	[0.19%]	[-1.5%]	[-0.72%]
Competitiveness(Normalized) Mean: Second Choices	0.2595	0.2322	0.2388	0.305
	[0.5594]	[0.5957]	[0.6447]	[0.6103]
Distance(Normalized) Mean: Second Choices	-0.6888	-0.5777	-0.4441	-0.0401
	[-0.0408]	[-0.0405]	[-0.0413]	[-0.0348]
STEM Concentration Share: Second Choices	43.76%	48.01%	50.12%	51.94%
	[-1.25%]	[2.87%]	[0.96%]	[1.7%]
Finance Concentration Share: Second Choices	7.53%	8.39%	9%	8.49%
	[-0.57%]	[-2.13%]	[2.48%]	[-0.55%]
Medical School Share: Second Choices	14.93%	11.72%	10.38%	9.31%
	[3.09%]	[0.86%]	[-1.46%]	[1.56%]
Competitiveness(Normalized) Mean: Third Choices	0.0612	0.0548	0.0596	0.0826
	[0.5172]	[0.5664]	[0.5809]	[0.5302]
Distance(Normalized) Mean: Third Choices	-0.6739	-0.5694	-0.4437	-0.05
	[0.0615]	[-0.0313]	[-0.1323]	[0.0346]
STEM Concentration Share: Third Choices	45.86%	49.38%	51.1%	51.92%
	[0.52%]	[1.3%]	[3.43%]	[0.48%]
Finance Concentration Share: Third Choices	7.61%	8.41%	8.82%	8.33%
	[-0.78%]	[0.26%]	[1.73%]	[-0.38%]
Medical School Share: Third Choices	11.41%	9.81%	9.4%	9.38%
	[0.46%]	[0.84%]	[0.9%]	[3.06%]
Competitiveness(Normalized) Mean: Fourth Choices	-0.5084	-0.4714	-0.4542	-0.5021
	[0.1248]	[0.2052]	[0.2517]	[0.1704]
Distance(Normalized) Mean: Fourth Choices	-0.6901	-0.6054	-0.4998	-0.081
	[0.3173]	[0.1424]	[0.0379]	[0.2216]
STEM Concentration Share: Fourth Choices	47.01%	49.9%	50.84%	48.12%
	[8.12%]	[10.14%]	[7.95%]	[2.78%]
Finance Concentration Share: Fourth Choices	8.08%	9.02%	9.38%	8.35%
	[3.65%]	[3.51%]	[3.86%]	[4%]
Medical School Share: Fourth Choices	10.58%	11.41%	11.49%	11.59%
	[-1.59%]	[2.06%]	[4.06%]	[3.49%]

Note: This table presents details of the fit of the model with distortion in subjective beliefs as in Section 8.1 and Table 6, Panel B. 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 B19: Fit of Benchmark Mixture Model with Subjective Beliefs: 40 - 60 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	55.15%	62.58%	65.1%	68.64%
	[6.6%]	[13.02%]	[10.14%]	[23.09%]
Mean Assignment Probability of 2nd Choice	68.29%	75.03%	77.26%	80.27%
	[3.33%]	[4.81%]	[3.2%]	[12.73%]
Mean Assignment Probability of 3rd Choice	74.92%	80.84%	82.4%	85.53%
	[-2.23%]	[-1.08%]	[-0.82%]	[5.9%]
Mean Assignment Probability of 4th Choice	83.52%	85.75%	86.19%	87.9%
	[-4.21%]	[-4.08%]	[-6.07%]	[-3.92%]
Share of Reversals $R \geq 75\%$	7.17%	6.81%	6.05%	5.3%
	[-6.68%]	[-2.41%]	[-1.49%]	[-1.58%]
Share of Reversals $R \geq 50\%$	17.38%	16.19%	15.27%	13.93%
	[-3.25%]	[0.78%]	[1.77%]	[-1.58%]
Share of Reversals $R \geq 25\%$	34.45%	32.46%	31.33%	28.91%
	[2.71%]	[7.03%]	[7.35%]	[1.99%]
Share of Reversals $R \geq 0\%$	60.35%	58.54%	57.75%	54.94%
	[-0.45%]	[2.18%]	[2.86%]	[-0.42%]
Competitiveness(Normalized) of Admitting College Mean	0.3651	0.3866	0.3918	0.4214
	[-0.0189]	[0.0188]	[0.0042]	[0.0581]
Share of Admission	97.04%	98.43%	98.56%	99.18%
	[1.02%]	[2.37%]	[1.01%]	[1.39%]
Competitiveness(Normalized) Mean: First Choices	-0.1703	-0.2574	-0.2918	-0.3128
	[-0.0632]	[-0.1131]	[-0.08]	[-0.2382]
Distance(Normalized) Mean: First Choices	-0.7895	-0.5435	-0.3846	-0.136
	[0.0361]	[-0.0331]	[0.0616]	[-0.0386]
STEM Concentration Share: First Choices	43.96%	45.4%	45.53%	44.37%
	[4.14%]	[1.19%]	[1.5%]	[-4%]
Finance Concentration Share: First Choices	7.74%	8.42%	8.24%	6.37%
	[0.33%]	[-0.24%]	[1.2%]	[-0.63%]
Medical School Share: First Choices	19.28%	16.33%	12.65%	6.75%
	[0.98%]	[2.16%]	[-1.44%]	[-4.2%]
Competitiveness(Normalized) Mean: Second Choices	-0.3432	-0.4266	-0.453	-0.4708
	[-0.0434]	[-0.0631]	[-0.0472]	[-0.1654]
Distance(Normalized) Mean: Second Choices	-0.8022	-0.5727	-0.4104	-0.1448
	[-0.1543]	[-0.0354]	[-0.0075]	[-0.1395]
STEM Concentration Share: Second Choices	42.28%	45.26%	45.89%	46.17%
	[-2.74%]	[0.12%]	[-3.27%]	[-4.07%]
Finance Concentration Share: Second Choices	7.92%	7.61%	7.23%	5.53%
	[-0.18%]	[-2.91%]	[0.71%]	[-3.51%]
Medical School Share: Second Choices	17.95%	17.98%	17.88%	16.21%
	[6.11%]	[7.12%]	[6.04%]	[8.46%]
Competitiveness(Normalized) Mean: Third Choices	-0.4514	-0.5352	-0.5495	-0.5655
	[0.0045]	[-0.0237]	[-0.0282]	[-0.118]
Distance(Normalized) Mean: Third Choices	-0.8365	-0.6091	-0.4399	-0.1734
	[-0.1011]	[-0.0711]	[-0.1285]	[-0.0889]
STEM Concentration Share: Third Choices	44.3%	47.23%	48.3%	48.25%
	[-1.05%]	[-0.85%]	[0.63%]	[-3.18%]
Finance Concentration Share: Third Choices	8.18%	7.49%	6.76%	4.83%
	[-0.21%]	[-0.66%]	[-0.32%]	[-3.89%]
Medical School Share: Third Choices	14.92%	12.85%	11.31%	8.73%
	[3.97%]	[3.89%]	[2.81%]	[2.4%]
Competitiveness(Normalized) Mean: Fourth Choices	-0.5818	-0.619	-0.6147	-0.6236
	[0.0514]	[0.0576]	[0.0912]	[0.049]
Distance(Normalized) Mean: Fourth Choices	-0.9042	-0.6342	-0.4629	-0.2072
	[0.1032]	[0.1136]	[0.0748]	[0.0955]
STEM Concentration Share: Fourth Choices	45.39%	50.37%	51.55%	53.34%
	[6.5%]	[10.61%]	[8.66%]	[8%]
Finance Concentration Share: Fourth Choices	8.31%	7.92%	7.35%	5.13%
	[3.88%]	[2.41%]	[1.83%]	[0.77%]
Medical School Share: Fourth Choices	16.11%	12.55%	10.66%	7.6%
	[3.95%]	[3.21%]	[3.23%]	[-0.5%]

Note: This table presents details of the fit of the model with distortion in subjective beliefs as in Section 8.1 and Table 6, Panel B. 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 B20: Fit of Benchmark Rational Model with Subjective Beliefs: 60 - 80 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	14.97%	14.54%	14.31%	14.12%
	[-39.17%]	[-38.57%]	[-38.64%]	[-31.36%]
Mean Assignment Probability of 2nd Choice	24.07%	22.97%	22.64%	22.44%
	[-46.04%]	[-50.39%]	[-49.63%]	[-47.29%]
Mean Assignment Probability of 3rd Choice	35.62%	34.42%	33.82%	33.87%
	[-44.88%]	[-49.66%]	[-51.53%]	[-48.49%]
Mean Assignment Probability of 4th Choice	77.7%	77.65%	77.66%	78.3%
	[-12.81%]	[-15.09%]	[-15.47%]	[-14.86%]
Share of Reversals $R \geq 75\%$	6.35%	5.54%	5.42%	5.7%
	[0.36%]	[2.61%]	[2.27%]	[3.07%]
Share of Reversals $R \geq 50\%$	15.25%	14.33%	14.49%	14.78%
	[0.75%]	[5.42%]	[6.55%]	[7.45%]
Share of Reversals $R \geq 25\%$	31.63%	30.9%	30.96%	30.69%
	[4.37%]	[11.98%]	[12.65%]	[13.21%]
Share of Reversals $R \geq 0\%$	63.49%	62.46%	61.96%	59.52%
	[8.8%]	[10.94%]	[12.93%]	[8.07%]
Competitiveness(Normalized) of Admitting College Mean	0.388	0.3787	0.3775	0.3901
	[-0.0753]	[-0.0078]	[0.01]	[0.0432]
Share of Admission	87.77%	87.52%	87.44%	87.66%
	[-9.79%]	[-10.4%]	[-10.53%]	[-10.98%]
Competitiveness(Normalized) Mean: First Choices	1.0101	1.0282	1.0498	1.142
	[0.6307]	[0.6093]	[0.631]	[0.5965]
Distance(Normalized) Mean: First Choices	-0.5299	-0.3242	-0.1907	0.0527
	[0.0482]	[-0.0043]	[-0.0128]	[-0.0264]
STEM Concentration Share: First Choices	45.72%	47.82%	48.86%	50.71%
	[5.21%]	[5.7%]	[4.51%]	[5.51%]
Finance Concentration Share: First Choices	9.09%	7.96%	7.32%	5.06%
	[1.45%]	[-3.16%]	[-0.31%]	[-1.74%]
Medical School Share: First Choices	13.5%	11.41%	9.94%	6.89%
	[-2.97%]	[-1.28%]	[-0.74%]	[-0.45%]
Competitiveness(Normalized) Mean: Second Choices	0.8295	0.8556	0.8768	0.9502
	[0.6366]	[0.6745]	[0.671]	[0.6504]
Distance(Normalized) Mean: Second Choices	-0.5237	-0.3165	-0.1775	0.074
	[-0.0033]	[-0.0314]	[0.043]	[0.022]
STEM Concentration Share: Second Choices	42.44%	45.29%	46.5%	49.3%
	[0.22%]	[-0.28%]	[0.44%]	[0.3%]
Finance Concentration Share: Second Choices	9.3%	8.43%	7.43%	5.7%
	[0.36%]	[-3.49%]	[-1.88%]	[-2.04%]
Medical School Share: Second Choices	15.51%	12.77%	11.48%	8.75%
	[1.7%]	[3.19%]	[0.52%]	[2.01%]
Competitiveness(Normalized) Mean: Third Choices	0.6465	0.6756	0.6981	0.7522
	[0.6245]	[0.6669]	[0.6817]	[0.6239]
Distance(Normalized) Mean: Third Choices	-0.5479	-0.3339	-0.1883	0.0809
	[-0.0566]	[0.0389]	[-0.0114]	[0.0313]
STEM Concentration Share: Third Choices	41.17%	44.4%	46.71%	50.21%
	[-3.37%]	[-2.56%]	[0.26%]	[-1.71%]
Finance Concentration Share: Third Choices	9.55%	8.88%	7.73%	6.06%
	[0.01%]	[-2.67%]	[-1.14%]	[-4.67%]
Medical School Share: Third Choices	16.51%	13.9%	12.63%	9.87%
	[5.11%]	[4.46%]	[2.92%]	[3.27%]
Competitiveness(Normalized) Mean: Fourth Choices	0.0911	0.1144	0.1268	0.1493
	[0.3269]	[0.3402]	[0.3566]	[0.294]
Distance(Normalized) Mean: Fourth Choices	-0.6824	-0.4078	-0.2382	0.0784
	[0.1725]	[0.1061]	[0.1036]	[0.152]
STEM Concentration Share: Fourth Choices	41.05%	47.06%	50.67%	55.4%
	[1.81%]	[2.73%]	[2.51%]	[6.61%]
Finance Concentration Share: Fourth Choices	8.5%	7.73%	6.96%	5.49%
	[-0.2%]	[-1.57%]	[0.2%]	[-4.18%]
Medical School Share: Fourth Choices	16.57%	14.2%	12.71%	11.17%
	[4.33%]	[2.48%]	[1.62%]	[4.39%]

Note: This table presents details of the fit of the model with distortion in subjective beliefs as in Section 8.1 and Table 6, Panel B. 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 B21: Fit of Benchmark Mixture Model with Subjective Beliefs: 60 - 80 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	67.55%	66.04%	65.61%	65.63%
	[13.41%]	[12.93%]	[12.65%]	[20.16%]
Mean Assignment Probability of 2nd Choice	77.31%	75.87%	75.25%	75.04%
	[7.2%]	[2.51%]	[2.98%]	[5.31%]
Mean Assignment Probability of 3rd Choice	82.21%	80.93%	80.18%	79.94%
	[1.71%]	[-3.15%]	[-5.18%]	[-2.42%]
Mean Assignment Probability of 4th Choice	85.9%	85.26%	84.73%	84.3%
	[-4.61%]	[-7.48%]	[-8.4%]	[-8.86%]
Share of Reversals $R \geq 75\%$	4.8%	5.13%	5.4%	5.56%
	[-1.19%]	[2.2%]	[2.24%]	[2.93%]
Share of Reversals $R \geq 50\%$	15.07%	15.49%	15.9%	16.3%
	[0.57%]	[6.58%]	[7.96%]	[8.97%]
Share of Reversals $R \geq 25\%$	35.38%	35.82%	36.61%	37.47%
	[8.12%]	[16.9%]	[18.3%]	[19.99%]
Share of Reversals $R \geq 0\%$	72.29%	71.91%	72.46%	73.19%
	[17.6%]	[20.38%]	[23.43%]	[21.74%]
Competitiveness(Normalized) of Admitting College Mean	0.4878	0.4901	0.4923	0.5069
	[0.0244]	[0.1036]	[0.1248]	[0.16]
Share of Admission	99.24%	99.14%	99.03%	98.79%
	[1.68%]	[1.22%]	[1.07%]	[0.15%]
Competitiveness(Normalized) Mean: First Choices	0.3007	0.3372	0.3515	0.3641
	[-0.0787]	[-0.0816]	[-0.0672]	[-0.1815]
Distance(Normalized) Mean: First Choices	-0.6115	-0.385	-0.2352	0.0511
	[-0.0335]	[-0.0652]	[-0.0572]	[-0.028]
STEM Concentration Share: First Choices	40.83%	43.92%	46.02%	49.54%
	[0.33%]	[1.8%]	[1.67%]	[4.34%]
Finance Concentration Share: First Choices	9.41%	9.32%	9.3%	8.65%
	[1.77%]	[-1.79%]	[1.67%]	[1.85%]
Medical School Share: First Choices	17.23%	12.69%	10.33%	6.57%
	[0.76%]	[0%]	[-0.35%]	[-0.77%]
Competitiveness(Normalized) Mean: Second Choices	0.1567	0.1918	0.2065	0.2122
	[-0.0362]	[0.0107]	[0.0008]	[-0.0876]
Distance(Normalized) Mean: Second Choices	-0.5904	-0.3596	-0.2212	0.0605
	[-0.0699]	[-0.0745]	[-0.0007]	[0.0085]
STEM Concentration Share: Second Choices	39.78%	43.29%	44.96%	48.69%
	[-2.44%]	[-2.28%]	[-1.1%]	[-0.31%]
Finance Concentration Share: Second Choices	8.98%	9.02%	8.92%	8.68%
	[0.04%]	[-2.89%]	[-0.39%]	[0.94%]
Medical School Share: Second Choices	16.64%	14.37%	13.63%	13.62%
	[2.83%]	[4.79%]	[2.68%]	[6.88%]
Competitiveness(Normalized) Mean: Third Choices	0.0444	0.0805	0.0982	0.104
	[0.0224]	[0.0718]	[0.0818]	[-0.0243]
Distance(Normalized) Mean: Third Choices	-0.6246	-0.3937	-0.2508	0.0389
	[-0.1333]	[-0.0209]	[-0.0738]	[-0.0107]
STEM Concentration Share: Third Choices	40.97%	44.39%	46.65%	50.76%
	[-3.58%]	[-2.57%]	[0.2%]	[-1.16%]
Finance Concentration Share: Third Choices	9.11%	9.16%	9.11%	8.74%
	[-0.43%]	[-2.39%]	[0.24%]	[-2%]
Medical School Share: Third Choices	15.63%	13.42%	11.82%	9.98%
	[4.23%]	[3.98%]	[2.11%]	[3.37%]
Competitiveness(Normalized) Mean: Fourth Choices	-0.0695	-0.0564	-0.036	0.001
	[0.1663]	[0.1694]	[0.1939]	[0.1457]
Distance(Normalized) Mean: Fourth Choices	-0.659	-0.4431	-0.3087	-0.0138
	[0.1959]	[0.0708]	[0.0331]	[0.0599]
STEM Concentration Share: Fourth Choices	44.29%	48.22%	50.79%	54.4%
	[5.05%]	[3.89%]	[2.64%]	[5.61%]
Finance Concentration Share: Fourth Choices	9.21%	9.32%	8.99%	9.09%
	[0.52%]	[0.02%]	[2.23%]	[-0.57%]
Medical School Share: Fourth Choices	14.79%	13.2%	12.23%	10.43%
	[2.56%]	[1.48%]	[1.14%]	[3.65%]

Note: This table presents details of the fit of the model with distortion in subjective beliefs as in Section 8.1 and Table 6, Panel B. 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 B22: Fit of Benchmark Rational Model with Subjective Beliefs: 80 - 100 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	25.78%	22.48%	20.56%	21.51%
	[-36.55%]	[-39.27%]	[-41.64%]	[-34.26%]
Mean Assignment Probability of 2nd Choice	39.86%	35.47%	34.11%	34.02%
	[-41.69%]	[-47.32%]	[-49.2%]	[-44.49%]
Mean Assignment Probability of 3rd Choice	55.09%	50.8%	49.83%	48.45%
	[-35.1%]	[-39.83%]	[-41.57%]	[-41.52%]
Mean Assignment Probability of 4th Choice	89.04%	87.59%	86.67%	86.62%
	[-6.06%]	[-8.79%]	[-10.32%]	[-9.97%]
Share of Reversals $R \geq 75\%$	14.44%	13.4%	12.92%	13.33%
	[11.62%]	[11.27%]	[11.45%]	[11.63%]
Share of Reversals $R \geq 50\%$	22.26%	21.47%	20.12%	19.77%
	[15.29%]	[16.91%]	[17.06%]	[15.94%]
Share of Reversals $R \geq 25\%$	32.32%	31.95%	31.08%	30.18%
	[16.04%]	[21.91%]	[20.76%]	[19.85%]
Share of Reversals $R \geq 0\%$	53.75%	53.16%	51.46%	48.92%
	[4.42%]	[8.78%]	[7.47%]	[8.35%]
Competitiveness(Normalized) of Admitting College Mean	0.587	0.5226	0.528	0.5693
	[0.164]	[0.1445]	[0.1788]	[0.2623]
Share of Admission	95.06%	93.89%	93.19%	93.58%
	[-3.35%]	[-4.89%]	[-6.13%]	[-6.14%]
Competitiveness(Normalized) Mean: First Choices	2.1015	2.1214	2.1734	2.3076
	[0.7956]	[0.7663]	[0.7508]	[0.6239]
Distance(Normalized) Mean: First Choices	-0.4147	-0.2681	-0.1996	0.0047
	[-0.0737]	[0.0453]	[-0.0523]	[-0.0277]
STEM Concentration Share: First Choices	27.13%	35.37%	37.42%	40.36%
	[-11.67%]	[-3.53%]	[2.61%]	[7.39%]
Finance Concentration Share: First Choices	7.52%	11.13%	11.97%	11.68%
	[-1.66%]	[1.41%]	[2.11%]	[2.11%]
Medical School Share: First Choices	12.96%	2.17%	0.7%	0.17%
	[2.93%]	[-7.4%]	[-6.45%]	[-4.54%]
Competitiveness(Normalized) Mean: Second Choices	1.7743	1.8259	1.8842	2.0525
	[0.7067]	[0.6926]	[0.699]	[0.6247]
Distance(Normalized) Mean: Second Choices	-0.3505	-0.2202	-0.1519	0.0111
	[-0.0238]	[-0.0231]	[-0.0613]	[-0.0319]
STEM Concentration Share: Second Choices	32.66%	40.5%	43.05%	45.34%
	[-9.52%]	[1.06%]	[0.75%]	[10.07%]
Finance Concentration Share: Second Choices	8.61%	12.45%	13.72%	13.11%
	[-0.32%]	[0.58%]	[4.75%]	[4.87%]
Medical School Share: Second Choices	13.94%	2.74%	0.88%	0.22%
	[4.76%]	[-5.89%]	[-4.75%]	[-3.3%]
Competitiveness(Normalized) Mean: Third Choices	1.4144	1.5002	1.5604	1.7599
	[0.4955]	[0.5371]	[0.5217]	[0.5184]
Distance(Normalized) Mean: Third Choices	-0.3007	-0.1695	-0.1099	0.0704
	[-0.0006]	[0.0295]	[-0.0103]	[0.0374]
STEM Concentration Share: Third Choices	37.41%	46.12%	48.62%	50.99%
	[-4.46%]	[-1.01%]	[6.34%]	[13.51%]
Finance Concentration Share: Third Choices	9.74%	13.71%	15.56%	15.51%
	[0.74%]	[3.94%]	[6.57%]	[6.47%]
Medical School Share: Third Choices	15.5%	3.15%	1.1%	0.18%
	[6.13%]	[-3.51%]	[-4.66%]	[-3.75%]
Competitiveness(Normalized) Mean: Fourth Choices	0.8197	0.9277	1.0004	1.106
	[0.1562]	[0.2434]	[0.2165]	[0.1249]
Distance(Normalized) Mean: Fourth Choices	-0.2204	-0.1285	-0.0683	0.0869
	[0.2171]	[0.1933]	[0.1083]	[0.0748]
STEM Concentration Share: Fourth Choices	42.17%	51.34%	53.59%	56.92%
	[0.96%]	[8.93%]	[13.07%]	[18.54%]
Finance Concentration Share: Fourth Choices	11.03%	16.08%	17.95%	18.18%
	[2.56%]	[5.16%]	[7.59%]	[10.84%]
Medical School Share: Fourth Choices	17.05%	3.32%	0.95%	0.12%
	[5.88%]	[-6.01%]	[-6.47%]	[-5.66%]

Note: This table presents details of the fit of the model with distortion in subjective beliefs as in Section 8.1 and Table 6, Panel B. 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 B23: Fit of Mixture Model with Subjective Beliefs: 80 - 100 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	73.03%	72.88%	72.06%	72.51%
Mean Assignment Probability of 2nd Choice	83.13%	82.92%	82.54%	83.19%
Mean Assignment Probability of 3rd Choice	86.64%	86.7%	86.83%	88.47%
Mean Assignment Probability of 4th Choice	90.24%	90.67%	91.14%	92.21%
Share of Reversals $R \geq 75\%$	4.3%	3.99%	3.84%	3.32%
Share of Reversals $R \geq 50\%$	12.37%	11.11%	10.03%	8.21%
Share of Reversals $R \geq 25\%$	29.09%	27.04%	24.56%	19.2%
Share of Reversals $R \geq 0\%$	68.84%	66.09%	62.05%	53.77%
Competitiveness(Normalized) of Admitting College Mean	0.4991	0.4957	0.505	0.521
Share of Admission	99.76%	99.78%	99.78%	99.8%
Competitiveness(Normalized) Mean: First Choices	1.223	1.2743	1.3461	1.5169
Distance(Normalized) Mean: First Choices	-0.397	-0.2407	-0.1281	0.0508
STEM Concentration Share: First Choices	46.44%	44.58%	43.4%	37.09%
Finance Concentration Share: First Choices	9.06%	8.88%	8.82%	7.42%
Medical School Share: First Choices	9.17%	5.22%	3.1%	0.95%
Competitiveness(Normalized) Mean: Second Choices	1.0462	1.1034	1.1878	1.3656
Distance(Normalized) Mean: Second Choices	-0.3579	-0.1952	-0.1042	0.0684
STEM Concentration Share: Second Choices	41.97%	42.2%	41.47%	35.86%
Finance Concentration Share: Second Choices	10.18%	10.55%	9.72%	9.03%
Medical School Share: Second Choices	11.11%	7.6%	5.09%	2.19%
Competitiveness(Normalized) Mean: Third Choices	0.9557	1.0088	1.084	1.2256
Distance(Normalized) Mean: Third Choices	-0.3463	-0.1864	-0.0941	0.0572
STEM Concentration Share: Third Choices	40.13%	39.58%	39.4%	35.44%
Finance Concentration Share: Third Choices	10.26%	10.26%	9.86%	9.49%
Medical School Share: Third Choices	11.95%	7.74%	5.69%	2.68%
Competitiveness(Normalized) Mean: Fourth Choices	0.8412	0.8882	0.9421	1.0635
Distance(Normalized) Mean: Fourth Choices	-0.3562	-0.212	-0.1276	0.0177
STEM Concentration Share: Fourth Choices	38.16%	38.43%	38.32%	37.62%
Finance Concentration Share: Fourth Choices	10.72%	10.5%	10.25%	9.71%
Medical School Share: Fourth Choices	12.06%	8.94%	6.68%	3.12%

Note: This table presents details of the fit of the model with distortion in subjective beliefs as in Section 8.1 and Table 6, Panel B. 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 B24: Value of Moments: 0 - 20 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	13.5% (0.57%)	15.78% (0.76%)	18.98% (0.8%)	14.89% (0.94%)
Mean Assignment Probability of 2nd Choice	23.69% (0.77%)	26.99% (0.99%)	30.05% (0.98%)	27.4% (1.28%)
Mean Assignment Probability of 3rd Choice	30.67% (0.85%)	34.23% (1.09%)	39.04% (1.08%)	36.9% (1.44%)
Mean Assignment Probability of 4th Choice	35.25% (0.91%)	40.9% (1.19%)	43.83% (1.13%)	42.63% (1.52%)
Share of Reversals $R \geq 75\%$	9.14% (0.69%)	10.43% (0.92%)	8.16% (0.79%)	9.4% (1.14%)
Share of Reversals $R \geq 50\%$	20.3% (0.97%)	20.07% (1.2%)	21.02% (1.18%)	18.21% (1.51%)
Share of Reversals $R \geq 25\%$	32.49% (1.12%)	32.8% (1.41%)	35.37% (1.39%)	31.64% (1.82%)
Share of Reversals $R \geq 0\%$	64.64% (1.15%)	64.19% (1.44%)	69% (1.34%)	64.93% (1.86%)
Competitiveness(Normalized) of Admitting College Mean	0.1252 (0.0025)	0.1261 (0.0032)	0.123 (0.0031)	0.1297 (0.0045)
Share of Admission	59.39% (1.18%)	63.84% (1.44%)	65.7% (1.38%)	65.52% (1.86%)
Competitiveness(Normalized) Mean: First Choices	-0.6989 (0.0117)	-0.7374 (0.0136)	-0.7655 (0.0133)	-0.6942 (0.0186)
Distance(Normalized) Mean: First Choices	-1.1642 (0.0052)	-0.8696 (0.0067)	-0.5751 (0.0067)	-0.2863 (0.0121)
STEM Concentration Share: First Choices	33.78% (0.69%)	36.87% (0.98%)	39.98% (0.95%)	45.52% (1.36%)
Finance Concentration Share: First Choices	2.88% (0.32%)	3.01% (0.43%)	2.8% (0.63%)	4.78% (1.18%)
Medical School Share: First Choices	14.44% (0.62%)	12.38% (0.8%)	10.31% (0.89%)	8.81% (1.25%)
Competitiveness(Normalized) Mean: Second Choices	-0.7966 (0.0111)	-0.8437 (0.0127)	-0.8673 (0.0126)	-0.8417 (0.0165)
Distance(Normalized) Mean: Second Choices	-0.9293 (0.0044)	-0.559 (0.0052)	-0.3825 (0.0061)	-0.1641 (0.0099)
STEM Concentration Share: Second Choices	41.04% (0.64%)	46.08% (0.83%)	47.24% (0.88%)	47.99% (1.11%)
Finance Concentration Share: Second Choices	1.71% (0.3%)	2.74% (0.53%)	2.94% (0.52%)	3.55% (1.16%)
Medical School Share: Second Choices	13.78% (0.59%)	10.1% (1.03%)	8.46% (1.02%)	6.02% (1.43%)
Competitiveness(Normalized) Mean: Third Choices	-0.8187 (0.0121)	-0.8889 (0.0122)	-0.922 (0.012)	-0.9182 (0.0148)
Distance(Normalized) Mean: Third Choices	-0.7243 (0.0038)	-0.4884 (0.0047)	-0.2763 (0.0051)	-0.1887 (0.0096)
STEM Concentration Share: Third Choices	44.49% (0.64%)	48.63% (0.78%)	49.72% (0.78%)	53.45% (1.13%)
Finance Concentration Share: Third Choices	1.7% (0.3%)	1.62% (0.4%)	2.39% (0.52%)	2.89% (0.91%)
Medical School Share: Third Choices	8.03% (0.69%)	6.6% (1%)	4.7% (1.01%)	4.98% (1.4%)
Competitiveness(Normalized) Mean: Fourth Choices	-0.8687 (0.0115)	-0.9376 (0.0108)	-0.9483 (0.0133)	-0.9317 (0.0169)
Distance(Normalized) Mean: Fourth Choices	-0.8288 (0.0038)	-0.5427 (0.0051)	-0.3377 (0.0058)	-0.1902 (0.0095)
STEM Concentration Share: Fourth Choices	42.8% (0.54%)	47.29% (0.71%)	49.75% (0.7%)	48.14% (0.92%)
Finance Concentration Share: Fourth Choices	1.98% (0.25%)	1.44% (0.44%)	1.5% (0.4%)	2.36% (0.74%)
Medical School Share: Fourth Choices	8.83% (0.66%)	6.64% (0.86%)	4.5% (0.93%)	3.89% (1.45%)

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 0th and 20th percentile among elite college eligible applicants. Standard errors are in the parenthesis.

Table B25: Value of Moments: 20 - 40 Percentile Test Score

Varname	SES Quarter (1st = Most Disadvantaged)			
	1st	2nd	3rd	4th
Mean Assignment Probability of 1st Choice	40.15%	41.64%	44.93%	37.62%
	(0.95%)	(1.11%)	(1.12%)	(1.39%)
Mean Assignment Probability of 2nd Choice	53.92%	61.52%	63.04%	60.24%
	(0.96%)	(1.1%)	(1.04%)	(1.34%)
Mean Assignment Probability of 3rd Choice	64.2%	69.35%	72.74%	70.52%
	(0.94%)	(1.07%)	(0.98%)	(1.27%)
Mean Assignment Probability of 4th Choice	74.05%	78.05%	80.29%	81.4%
	(0.86%)	(0.99%)	(0.87%)	(1.07%)
Share of Reversals $R \geq 75\%$	11.2%	7.82%	7.01%	9.54%
	(0.82%)	(0.85%)	(0.78%)	(1.13%)
Share of Reversals $R \geq 50\%$	27.7%	19.9%	19.29%	20.09%
	(1.16%)	(1.27%)	(1.2%)	(1.54%)
Share of Reversals $R \geq 25\%$	44.93%	38.02%	36.49%	35.12%
	(1.29%)	(1.54%)	(1.47%)	(1.83%)
Share of Reversals $R \geq 0\%$	72.3%	70.79%	68.88%	69.94%
	(1.16%)	(1.45%)	(1.41%)	(1.76%)
Competitiveness(Normalized) of Admitting College Mean	0.2591	0.2604	0.2716	0.2391
	(0.0048)	(0.0063)	(0.0059)	(0.0073)
Share of Admission	91.52%	91.09%	90.81%	91.76%
	(0.72%)	(0.91%)	(0.88%)	(1.06%)
Competitiveness(Normalized) Mean: First Choices	-0.4858	-0.534	-0.5554	-0.457
	(0.0131)	(0.0135)	(0.0139)	(0.0192)
Distance(Normalized) Mean: First Choices	-0.9285	-0.7015	-0.3758	-0.1225
	(0.0082)	(0.0088)	(0.0091)	(0.0141)
STEM Concentration Share: First Choices	37.77%	44.36%	43.04%	47.11%
	(0.8%)	(1.06%)	(1.05%)	(1.27%)
Finance Concentration Share: First Choices	6.3%	6.83%	6.1%	6.5%
	(0.38%)	(0.57%)	(0.73%)	(1.06%)
Medical School Share: First Choices	13.25%	11.39%	11.01%	7.66%
	(0.71%)	(0.92%)	(1.03%)	(1.41%)
Competitiveness(Normalized) Mean: Second Choices	-0.6407	-0.7164	-0.739	-0.6807
	(0.0113)	(0.0109)	(0.0101)	(0.0148)
Distance(Normalized) Mean: Second Choices	-0.8402	-0.5653	-0.2974	-0.0721
	(0.0061)	(0.0082)	(0.0085)	(0.0119)
STEM Concentration Share: Second Choices	42.87%	46.39%	45.59%	53.37%
	(0.84%)	(1.11%)	(1.08%)	(1.32%)
Finance Concentration Share: Second Choices	3.97%	4.52%	4.96%	4.55%
	(0.38%)	(0.5%)	(0.66%)	(1.07%)
Medical School Share: Second Choices	13.32%	8.73%	9.19%	6.16%
	(0.79%)	(1.06%)	(1%)	(1.38%)
Competitiveness(Normalized) Mean: Third Choices	-0.7246	-0.775	-0.8185	-0.7801
	(0.011)	(0.0117)	(0.0099)	(0.013)
Distance(Normalized) Mean: Third Choices	-0.7667	-0.5675	-0.2697	-0.1617
	(0.0063)	(0.0066)	(0.0069)	(0.0109)
STEM Concentration Share: Third Choices	44.28%	48.71%	47.21%	52.02%
	(0.82%)	(1.03%)	(0.96%)	(1.29%)
Finance Concentration Share: Third Choices	3.84%	3.4%	4.16%	3.89%
	(0.37%)	(0.48%)	(0.65%)	(1.02%)
Medical School Share: Third Choices	8.09%	5.66%	5.01%	4.33%
	(0.75%)	(1.06%)	(1.01%)	(1.31%)
Competitiveness(Normalized) Mean: Fourth Choices	-0.8277	-0.8687	-0.9116	-0.9054
	(0.0102)	(0.0107)	(0.0083)	(0.0099)
Distance(Normalized) Mean: Fourth Choices	-0.9353	-0.743	-0.4952	-0.2651
	(0.0045)	(0.0057)	(0.0055)	(0.0096)
STEM Concentration Share: Fourth Choices	40.3%	44.31%	45.94%	48.3%
	(0.66%)	(0.82%)	(0.89%)	(1.1%)
Finance Concentration Share: Fourth Choices	2.14%	2.13%	2.06%	3.25%
	(0.27%)	(0.49%)	(0.47%)	(0.95%)
Medical School Share: Fourth Choices	7.68%	5.31%	5.58%	4.02%
	(0.71%)	(0.99%)	(1.05%)	(1.43%)

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 20th and 40th percentile among elite college eligible applicants. Standard errors are in the parenthesis.

C Details of Structural Estimation

This section lays out the details on the specification and the moments we use for the structural estimation in Section 7 and 8.1.

Remember 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 5, 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 $C_j \equiv 10 * (NC_j - \min_{j \in \text{elite college}} \{NC_j\})$ 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

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

D Revealed Preference Implication of Reversals

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 1 *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

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

As $p_B(\cdot)$ 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*

$$\text{sgn}((p_X(s_1) - p_Y(s_1)) \neq \text{sgn}((p_X(s_2) - p_Y(s_2)))$$

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 1 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, \dots, 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 $\mathcal{C}_{(u, A, \kappa)}^{RN} = \{s | \mathcal{R}(u, A, s) = \kappa\}$ is the contour set of priority score s where A is listed as at position κ under Rational Decision Rule and preference u .
- Set $\mathcal{C}_{(u, A, \kappa)}^{DC} = \{s | \mathcal{D}(u, A, s) = \kappa\}$ is the contour set of priority score s where A is listed as at position κ under Rational Decision Rule and preference u .

Proposition 2 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

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

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 3 *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

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

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 2 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 2. 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 2.

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 2 are impossible to hold at the same time.

If $N = X$, $M \neq W$ because of proposition 2. 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 2.

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 1.

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 2.

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 1.

Proof of Scenario 6 concludes.

■

Proposition 4 Under Assumption 1, 2, 3, for any preference profile u , college A , $\mathcal{C}_{(u, A, \kappa)}^{RN} \equiv \{s | \mathcal{R}(u, A, s) = \kappa\}$ 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 2.

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 2.

■

Remark Proposition 2 and 3 together imply Theorem 1.

Proposition 5 *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; if $p_X(s) > p_A(s)$, 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 5 implies Theorem 2.

Proposition 6 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,

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

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

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

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

■

Remark Proposition 6 provides the intermediate results for Theorem 3.