Transparency and Information Acquisition in College Admissions*

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Abstract

We theoretically and experimentally study centralized college admissions in which colleges evaluate students under a 'translucent' admission system and students can learn each college's suitability through costly information acquisition. In centralized matching via Gale and Shapley's deferred acceptance algorithm, students must decide whether to acquire information before submitting their rank-order lists. However, uncertainty about the final assignment lowers the expected gain from learning, thereby reducing social welfare, compared to a scenario without such uncertainty. Our experiments demonstrate that the welfare loss is greater with more opaque admission systems. The empirical social welfare obtained in our experimental treatments is consistently lower than the theoretical welfare, and we identify non-equilibrium learning as a main contributor.

Keywords: College admissions, Admission uncertainty, Information acquisition, Timing of learning, Laboratory experiments

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1 Introduction

In college admissions markets, students often face multiple forms of uncertainty. In particular, they face *admission uncertainty*, which arises from students' inability to precisely assess

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their admission chances at the time of application, and *preference uncertainty*, which stems from their initial lack of information about how well each college fits them. We study a centralized college admissions environment in which colleges rank applicants by caliber, yet students do not know their exact position in the priority order when they submit their rank-order lists (ROLs). Crucially, students can mitigate preference uncertainty by engaging in costly information acquisition before submitting their ROLs. Our analyses, both theoretical and experimental, investigate how admission uncertainty interacts with students' incentives to acquire such information.

Admission uncertainty is pervasive in practice, as colleges typically rely on evaluation components that students cannot fully observe or translate into precise admission probabilities (e.g., essays, recommendation letters, or interviews). Consequently, students often cannot precisely predict their admission chances in advance, though the degree of uncertainty varies with the transparency of the admission system. For instance, students in China and Australia experience limited admission uncertainty because they have access to their final scores and admission priorities. In most Chinese provinces, students submit their ROLs after learning their National College Entrance Exam (*gaokao*) scores, which are the primary determinant of priority (Chen and Kesten, 2017). In Victoria, Australia, applicants submit initial ROLs and may revise them after receiving their Equivalent National Tertiary Entrance Rank (ENTER) scores, which are the sole determinant of admission for most applicants (Artemov, Che, and He, 2020). In contrast, students in France face greater uncertainty because colleges evaluate applicants based on multiple factors—such as high school GPA, grades in specific subjects, and qualitative assessments—making it difficult for applicants to assess their priority or exact admission chances (Hakimov, Schmacker, and Terrier, 2023).[1]

Resolving preference uncertainty requires students to uncover idiosyncratic attributes that are difficult to observe ex ante and are valued differently across students—such as program content, campus culture, location and living arrangements, and career networks. This learning process is intricate and resource-intensive. For example, many universities host undergraduate information days and campus tours, which are designed to furnish prospective students and their parents with details about their academic programs. Students also seek information through open classes, conversations with current students and alumni, and online reviews or social media. However, acquiring such information across all relevant colleges is typically costly, both in terms of money and time, forcing students to selectively invest in gathering information about specific colleges.[2]

[1]We thank an anonymous referee for bringing these examples to our attention.

[2]Visiting colleges and universities in expensive cities in the US can cost $2,000 for one trip in 2021. See "Set a Budget for College Tours" by Farran Powell in the USNews (`https://www.usnews.com/education/best-colleges/articles/2016-07-12/set-a-budget-for-college-tours`) and "Col-

Our model highlights that students' incentives to acquire information are influenced not only by the costs of obtaining information but also by the admission uncertainty. Formally, we consider an admission system that employs the deferred acceptance (DA) algorithm proposed by Gale and Shapley (1962), with two colleges and a unit mass of students. Each college has a limited capacity, and each student possesses an exam score that is privately observed. This score aggregates all pertinent factors known to the student, including their ACT/SAT scores or high school GPAs. Colleges evaluate students based on final scores, which are unobserved by students and *imperfectly* correlated with their exam scores. All students have the same prior beliefs about the colleges, reflecting academic quality or public school rankings, but each student can learn about individual preferences or suitability for the colleges by incurring costs. Accordingly, students' college rankings may change based on the information they acquire.

The DA mechanism requires students to submit their preference rankings over the colleges, and so students acquire information before submitting their ROLs. In equilibrium, students' information acquisition follows simple threshold rules: students learn about a college when the learning cost is low, and then learn about the other college when the first learned suitability is neither too high nor too low. Moreover, the DA allocation can be summarized by cutoff final scores, so that students with high final scores are assigned to their top-ranked college, whereas those with intermediate scores are assigned to the other college. Despite this general structure of information acquisition, the intensity of learning varies with admission uncertainty, which in turn depends on the extent to which final scores are correlated with the exam scores that students possess. For instance, if the final scores are perfectly correlated with students' exam scores, students can infer their admission prospects from their exam scores, effectively eliminating admission uncertainty. In contrast, if the final scores are completely random, even students with high exam scores will still experience significant admission uncertainty.

To examine how admission uncertainty affects students' information acquisition incentives and welfare, we compare DA with a hypothetical benchmark admission system in which students make learning decisions after knowing their admission outcomes. In our stylized framework, the benchmark is implemented through a simple version of decentralized matching in which students apply to colleges without incurring application costs, colleges admit students based on their final scores, and students then choose among the colleges that admitted them.[3] In this benchmark, it is straightforward that students would acquire information

lege Visit Expenses: Don't Overlook These Smaller Costs" by Melissa Brock (`https://collegefinance.com/college-admissions/college-visit-expenses-dont-overlook-these-smaller-costs`).

[3]It is not necessary that the benchmark be implemented by such a decentralized matching. We discuss alternative matching mechanisms that yield the same outcome in Remark 2.

after being admitted by both colleges. The idea is that, once students acquire information after knowing where they are admitted, and thereby face no admission uncertainty, then the transparency of the admission system should not affect their learning decisions. Moreover, allocations in this benchmark are characterized by cutoff scores: high-final score students are admitted by both colleges, while mid-final score students are admitted by only one. This allows for a clear comparison of students' learning behavior under DA and the benchmark.

Building on this comparison, we show that admission uncertainty generates differences in learning behavior between DA and the benchmark along two margins: who learns the suitability (*extensive learning margin*) and how much information they acquire (*intensive learning margin*). First, conditional on learning about one college, students in DA have weaker incentives to learn about the other college because they remain uncertain about their final assignment, lowering the intensive learning margin. Second, under DA, students must weigh learning costs against admission probabilities, so the extensive learning margin varies with the learning cost, whereas in the benchmark, only those admitted by both colleges learn, who face no admission uncertainty. Thus, when the learning cost is high, only students with high exam scores learn under DA, reducing the extensive learning margin. When the cost is low, however, students with lower exam scores start to learn, but the welfare gains from this expansion are limited because they are less likely to be assigned to their top choices. Consequently, in both cases, students' overall welfare under DA is lower than under the benchmark.

While the theoretical analysis predicts lower welfare under DA relative to the benchmark, the effect of translucent admissions on students' learning decisions is complex. As the correlation between final scores and exam scores weakens, students with lower exam scores may realize high final scores and thus have stronger incentives to learn, while those with high exam scores become more likely to realize lower final scores, reducing their incentives to acquire information. To develop optimal learning strategies, as suggested by the theoretical analysis, students must form accurate beliefs about admission probabilities, which depend on the learning decisions of other students as well as their own exam scores. This task is quite challenging for students in real life, leading them to potentially behave sub-optimally, which necessitates an empirical analysis.

We propose an experimental design to study how admission uncertainty, arising from the timing of learning and the transparency of admission systems, provides different incentives for students to acquire information. We implement our experiment with four treatments: a treatment with high transparency (i.e., final scores are more correlated with exam scores) and a treatment with low transparency (i.e., final scores are less correlated with exam scores) for each of DA and the benchmark system. We develop a simple experimental environment that allows us to observe *whether* each individual subject acquires information about one or both colleges, *how* this is influenced by the transparency of admission systems, and *when* the information is acquired.[4]

We find that the observed learning behaviors in our experiment are largely consistent with the theoretical predictions. First, under DA, most students learned before submitting their top-choice colleges, unless their exam scores were so low that they had no chance to be admitted by the "better" college (having a higher admission cutoff). Second, in the benchmark, most students learned after being admitted by both colleges, unless their exam scores are so high that they will surely be admitted by any college they apply to. Across all treatments, students who had already learned the suitability of one college further learned the suitability of the other college substantially more often when the suitability of the first college was neither too high nor too low, as the theory suggests. However, inconsistent with theory but in line with findings from the recent experimental studies on school choice (e.g., Chen and He, 2021b; Hakimov, Kübler, and Pan, 2023), we observe deviations from the equilibrium learning. Both over-learning and under-learning occurred, though under-learning was more frequent and of greater magnitude.

Our experimental data confirm the key welfare implication of our model. When the transparency is high, the empirical social welfare obtained in DA is not significantly different from that in the benchmark admission system. However, when the transparency is low, the empirical social welfare obtained in DA is significantly smaller than that in the benchmark admission system. Nevertheless, social welfare obtained in each of our experimental treatments was consistently lower than the theoretical welfare level. The observed discrepancy is due not only to the non-equilibrium learning discussed above but also other types of non-equilibrium decisions, including mistakes in the top-choice college submission in DA and in the application decisions in the benchmark, and mistakes in the attendance decisions. We decompose the welfare losses (relative to the equilibrium predictions) and identify that non-equilibrium learning is the main contributor to the observed welfare loss in all treatments.

Our findings suggest that admissions policies that reduce uncertainty—through greater transparency or disclosure of relevant information—can improve students' information acquisition and welfare. They also highlight that when optimal behavior requires sophisticated beliefs about admission probabilities, complementary interventions that simplify or standardize information may be necessary.

[4]Specifically, we separate individuals' learning decisions from all other decisions including the choice of the top college in DA and the application decision in the benchmark by providing two decision panels that run independently on their screen. See Section 3 for more details.

Related literature.

Previous studies in the matching literature have examined how costly information acquisition affects matching outcomes in college admissions. Chen and He (2021a) theoretically analyze students' incentives under DA and the Boston (Immediate Acceptance) mechanisms, showing that students have an incentive to learn their own cardinal and others' preferences only under the Boston mechanism. Chen and He (2021b) is an experimental companion paper to Chen and He (2021a). Unlike theirs, our paper does not compare different matching mechanisms. It also differs in learning technologies: students in their setting can learn both their own and others' preferences, whereas students in ours can only learn their own. Nevertheless, consistent with their findings, we also observe suboptimal learning in the laboratory.

Our work aligns with Artemov (2021) and Hakimov, Kübler, and Pan (2023) in exploring the effects of admission uncertainty on welfare.[5] Artemov (2021) shows that in the random serial dictatorship (RSD), students gather less information than the social optimum. He also suggests policies to reduce admission uncertainty, thereby enhancing students' welfare. Our model incorporates RSD and the serial dictatorship (SD) as special cases when the final scores are fully random or perfectly correlated with exam scores, respectively. We show that SD results in higher welfare than RSD as consistent with Artemov (2021).

Hakimov, Kübler, and Pan (2023) compare students' learning incentives under two variants of serial dictatorship: direct SD, where students submit their ROLs in advance, and sequential SD, where students choose colleges sequentially in priority order without initially submitting ROLs. They show that the sequential SD improves students' welfare by eliminating admission uncertainty. While our findings are consistent with theirs in showing welfare gains from reducing uncertainty, the underlying mechanisms differ. Their model assumes that colleges are grouped into distinct "tiers," with all students strictly preferring any college in a higher tier and colleges within a tier being ex-ante symmetric. In this setting, the sequential SD makes students acquire *less* information by forcing them to focus on the best available tier at the timing of learning, thereby avoiding wasteful information acquisition. In contrast, our model allows for ex-ante asymmetry across colleges, and students' preferences can be reversed depending on learning outcomes. As a result, in our benchmark model, students are encouraged to acquire *more* information, which improves the quality of student-college matches and leads to higher overall welfare.

Our paper also contributes to the broader literature on search and matching with incomplete information in the context of college admissions.[6] Immorlica, Leshno, Lo, and Lucier

[5] See also Bade (2015) who shows that in a house allocation problem, serial dictatorship makes agents know their exact choice set when they make learning decisions and proves that it is the unique Pareto-optimal, strategy-proof, and non-bossy mechanism when agents may acquire information on their own preferences.

[6] See Chade, Eeckhout, and Smith (2017) for a recent survey of this literature.

(2020) model students' information acquisition as a sequential search problem and introduce "regret-free stability" under costly information acquisition.[7] While they establish the existence of such outcomes, they abstract from the detailed process of students' information acquisition. Our work complements theirs by providing a full equilibrium characterization under specific admission mechanisms. Grenet, He, and Kübler (2022) provide empirical evidence from Germany's university admissions system, showing that students are more likely to accept early offers because holding (multiple) early offers prompts them to invest more time in learning about universities. This aligns with our results that students are more likely to acquire information when they are more likely to be admitted by both colleges. Chade, Lewis, and Smith (2014) study students' application strategies when application is costly and colleges observe noisy signals of student ability. While their framework shares with ours the feature that students' strategic decisions affect their admission outcomes, their focus is on application portfolio choices—how students choose the set of colleges to apply—whereas our focus is on the timing and content of learning decisions. Importantly, we conduct a novel comparative statics analysis on the transparency of admission systems within an experimental setting.

Our notion of the imprecision of final scores relates to the extent to which they reflect students' exam scores. A few recent papers investigate how noisy exam scores (corresponding to our final scores)—used as a single measure of students' abilities (corresponding to our exam scores)—affect matching outcomes under different centralized mechanisms. Lien, Zheng, and Zhong (2017) compare the Boston mechanism and serial dictatorship, investigating how these mechanisms achieve ex-ante fairness when admission decisions rely on exam scores that may not perfectly reveal true ability. Lien, Zheng, and Zhong (2016) bring this comparison to the laboratory, highlighting the importance of the timing of preference submission (pre-exam vs. post-exam) created by different mechanisms. Pan (2019) provides evidence from the field and laboratory that pre-exam preference submission in the Boston mechanism cannot fully resolve issues created by the exam's measurement error.

Our findings on ranking and attendance mistakes in the experiment align with patterns of student behavior under DA documented in recent studies. Regarding ranking mistakes, Chen and Sönmez (2006) find that about 36% of participants misrepresent their preferences in a laboratory setting. More recent studies—Artemov, Che, and He (2023), Hassidim, Romm, and Shorrer (2021), and Shorrer and Sóvágó (2023)—report that 17% to 35% of applicants misrepresent their preferences in college admissions using DA in Australia, Israel,

[7] They define an outcome to be stable if no student can form a blocking pair with a college or would wish to collect more information, and *regret-free stable* if it is stable and each student has acquired information optimally.

and Hungary, respectively. Attendance mistakes are also related to Narita (2018), who documents that about 7% of NYC high school applicants do not pursue their assigned schools but enter a secondary matching process, often due to newly acquired information about school characteristics or a revised understanding of their own preferences. This parallels our finding that attendance mistakes are closely associated with suboptimal learning.

The remainder of the paper is organized as follows. Section 2 develops the model and analyzes students' learning behavior and welfare implications. Section 3 describes the experimental design and presents testable hypotheses, and Section 4 reports experimental findings. Section 5 concludes. Proofs are relegated to Appendix A. Appendix B presents the extension of our model to three colleges. Additional figures and the experimental instructions are provided in Appendices C and D.

2 Theoretical Analysis

In this section, we develop a theoretical model to analyze students' learning behavior under DA. We then introduce a benchmark admission system and examine the welfare implications of admission uncertainty.

2.1 Model

There are two colleges, 1 and 2, and a unit mass of students. Each college $i = 1, 2$ has capacity $k < \frac{1}{2}$ and quality q_i, with $\Delta := q_1 - q_2 \geq 0$ commonly known. Each student is characterized by $(\alpha, \epsilon_1, \epsilon_2)$. Here, α represents the exam score drawn from a distribution F on $[\underline{\alpha}, \overline{\alpha}]$, capturing academic performance or attributes such as ACT/SAT scores or high school GPA. Each student privately observes her own exam score α. The term ϵ_i denotes the student's idiosyncratic preference, or "suitability," for college i; the ϵ_i's are independent of each other and of α. A student's ex-post value from attending college i is $v_i = q_i + \epsilon_i$, meaning the student enjoys an extra payoff ϵ_i, in addition to the common quality q_i.

Although each student's exam score α is privately known, the idiosyncratic preferences ϵ_i are initially unknown. Each student may learn ϵ_i by paying a cost c, with learning occurring sequentially: she may learn one ϵ_i , observe its realization, and then decide whether to learn the other. If learned, each ϵ_i is drawn independently from a distribution G on $[-\delta, \delta]$, where G is continuous, strictly increasing, and symmetric around zero. Consequently, the student's value of college i becomes $q_i + \epsilon_i$ if learned, and remains q_i otherwise. We assume $q_2 > \delta$ so attending either college is better than not attending, and $\Delta < 2\delta$ to avoid the trivial case where all students prefer college 1 regardless of the realizations of ϵ_1 and ϵ_2.

Colleges rank applicants based on a final evaluation score, denoted by s. This score is unobserved by students but is *imperfectly* correlated with their observable exam score α. Specifically, the final score of a student with exam score α is given by

$$s = r\,\alpha + (1 - r)\,\theta,$$

where $r \in [0, 1)$ is a constant and $\theta \sim U[-\eta, \eta]$ represents an evaluation noise or adjustment term. Note that while we refer to α as the exam score, it effectively aggregates all student-observed attributes. In contrast, the final score s incorporates unobserved evaluation components—such as essays, letters, and interviews—reflecting the reality that colleges assess more than just academic caliber. In this sense, the parameter r measures the degree of transparency: while students with higher α are more likely to have higher final scores, students remain uncertain about their exact priority due to the noise θ.

We consider a centralized admission system using DA in which students submit rank-order lists (ROLs) to a clearinghouse that simulates the following procedure. In the first round, students apply to their top choice, and colleges tentatively accept applicants with the highest scores up to capacity and permanently reject the rest. In each subsequent round, rejected students apply to their next choice, and colleges re-evaluate all currently admitted students and new applicants based on their final scores, again tentatively accepting top students and rejecting the rest. This process continues until there are no more rejections.

The timing is as follows. At $t = 0$, students observe their own α (but not s) and choose whether to learn ϵ_1 and/or ϵ_2 or neither. At $t = 1$, students simultaneously submit their ROLs. At $t = 2$, the clearinghouse determines the assignments. Finally, at $t = 3$, students decide whether to enroll in their assigned colleges.

2.2 Equilibrium Characterization

We begin with two remarks. First, since DA makes truthful reporting a weakly dominant strategy for students (Dubins and Freedman, 1981; Roth, 1982), students rank $i \succ j$ if and only if the expected value of college i exceeds that of college j.[8] Second, with a continuum of students, the DA outcome is characterized by cutoff scores $(\hat{s}_1, \hat{s}_2)$ (Azevedo and Leshno, 2016). Suppose $\hat{s}_1 > \hat{s}_2$ (verified later) and consider a student who submits $1 \succ 2$. If $s \geq \hat{s}_1$, she is accepted by college 1 in the first round and remains there. If $s \in [\hat{s}_2, \hat{s}_1)$, she is rejected by college 1 in the first round but accepted by college 2 in the second round. If $s < \hat{s}_2$, she

[8] We assume that if a student is indifferent between colleges, she randomly chooses one to rank higher. Such indifference arises if (i) she learns only ϵ_i and finds $q_i + \epsilon_i = q_j$, or (ii) she learns both ϵ_1 and ϵ_2 and finds $q_1 + \epsilon_1 = q_2 + \epsilon_2$. Both occur with probability zero, so we do not explicitly consider them in what follows.

is rejected by both. Similarly, a student submitting $2 \succ 1$ is accepted by college 2 and is retained whenever $s \geq \hat{s}_2$. Hence, students with $s \geq \hat{s}_1$ are assigned to their top-choice college, while those with $s \in [\hat{s}_2, \hat{s}_1)$ are assigned to college 2 regardless of their ROLs.

The following theorem characterizes equilibrium learning and ROL submission decisions.

Theorem 1. *There exists a unique equilibrium in which $\hat{s}_1 > \hat{s}_2$ and students' learning and ROL submission decisions are as follows: for each α, there exist $\bar{c}(\alpha)$ and $\bar{\epsilon}(\alpha)$ such that*

(i) for $c \geq \bar{c}(\alpha)$, students do not learn the suitability and submit $1 \succ 2$.

(ii) for $c < \bar{c}(\alpha)$, students learn ϵ_i for some i, and then they submit

- *(a) $i \succ j$ without learning ϵ_j if $\epsilon_i \geq \bar{\epsilon}(\alpha) + (i-j)\Delta$;*
- *(b) $i \succ (\prec) j$ when $q_i + \epsilon_i > (<) q_j + \epsilon_j$ after learning ϵ_j additionally if $|\epsilon_i + (i-j)\Delta| < \bar{\epsilon}(\alpha)$;*
- *(c) $j \succ i$ without learning ϵ_j if $\epsilon_i \leq -\bar{\epsilon}(\alpha) + (i-j)\Delta$.*

Proof. See Appendix A.1. ∎

To understand students' learning behavior, consider a student with exam score α who has already learned ϵ_1. If she does not learn ϵ_2, then the expected values of colleges are $\mathbb{E}[v_1|\epsilon_1] = q_1 + \epsilon_1$ and $\mathbb{E}[v_2|\epsilon_1] = q_2$. Her expected payoff is

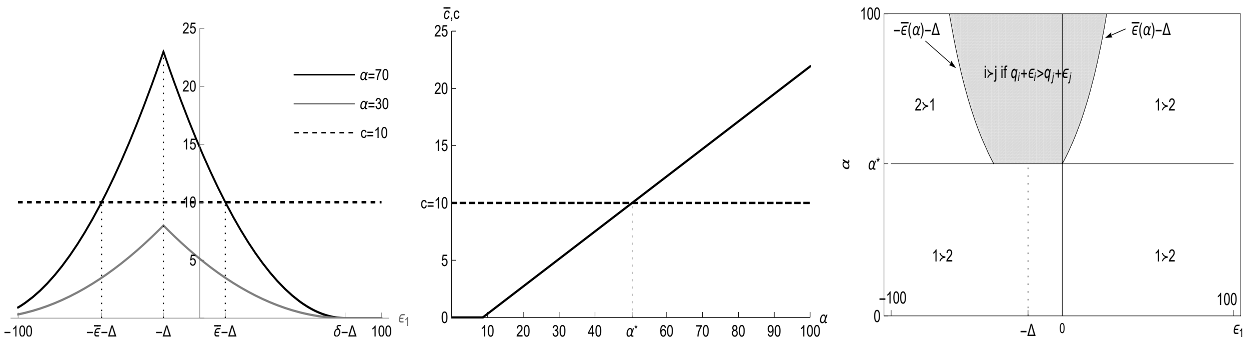
$$u(\epsilon_1; \alpha) = Q_2(\alpha) q_2 + Q_1(\alpha)\big(\Delta + \epsilon_1\big)\mathbb{1}_{\{\epsilon_1 > -\Delta\}},$$

where $Q_i(\alpha) := \text{Prob}(s \geq \hat{s}_i | \alpha)$ is the probability that her final score exceeds $\hat{s}_i$, and $\mathbb{1}_{\{.\}}$ is the indicator function. The first term reflects the baseline payoff from college 2, received with probability $Q_2(\alpha)$, regardless of her ranking. The second term captures the additional payoff from ranking college 1 first when $\epsilon_1 > -\Delta$, in which case she is admitted to college 1 with probability $Q_1(\alpha)$ and gains $(q_1 + \epsilon_1) - q_2 = \Delta + \epsilon_1$ relative to attending college 2. Next, suppose that the student chooses to learn ϵ_2 as well. She will then rank $i \succ j$ if $q_i + \epsilon_i > q_j + \epsilon_j$. After some algebra, her expected payoff can be written as

$$u(\epsilon_2|\epsilon_1; \alpha) = Q_2(\alpha) q_2 + Q_1(\alpha) \int_{-\delta}^{\epsilon_1 + \Delta} (\Delta + \epsilon_1 - \epsilon_2) dG(\epsilon_2).$$

Again, the first term reflects the expected payoff from college 2, while the second term captures the expected additional gain from ranking college 1 first.

The difference $u(\epsilon_2|\epsilon_1; \alpha) - u(\epsilon_1; \alpha)$ represents the expected gain from learning ϵ_2 given ϵ_1. Thus, the student learns it if and only if this gain exceeds c, which is equivalent to $\epsilon_1 \in (-\bar{\epsilon}(\alpha) - \Delta, \bar{\epsilon}(\alpha) - \Delta)$ for some threshold $\bar{\epsilon}(\alpha)$. Panel (a) of Figure 1 illustrates this relationship. For a given α, the gain from learning is small when ϵ_1 is either high enough to prefer college 1 or low enough to prefer college 2, even without learning ϵ_2. Accordingly, she



(a) Learning ϵ_2 after observing ϵ_1 (b) Learning decision for ϵ_1 (c) ROL submissions

Figure 1: **Learning and ROL submission decisions in DA.** Parameters: $\alpha \sim U[0,100]$, $\theta \sim U[-100,100]$, $\epsilon_i \sim U[-100,100]$, $\Delta = 20$, $k = r = 0.4$, $c = 10$. The resulting equilibrium values are $(\hat{s}_1, \hat{s}_2) \simeq (45.21, 30.98)$, $\overline{c}(\alpha) = \max\{0.24\alpha - 2.08, 0\}$, and α^*. Panel (a) depicts $u(\epsilon_2|\epsilon_1;\alpha) - u(\epsilon_1;\alpha)$ (solid curves). Panel (b) shows $\overline{c}(\alpha)$ (solid line) and $\alpha^* \simeq 50.35$. The dashed lines in (a) and (b) indicate the cost c. In panel (c), the gray region represents students with α who have learned $\epsilon_1 \in (-\overline{\epsilon}(\alpha) - \Delta, \overline{\epsilon}(\alpha) + \Delta)$.

does not learn ϵ_2 and submits $1 \succ 2$ if $\epsilon_1 \geq \overline{\epsilon}(\alpha) - \Delta$, or $2 \succ 1$ if $\epsilon_1 \leq -\overline{\epsilon}(\alpha) - \Delta$. For intermediate values, she learns ϵ_2 and ranks the college with the higher realized value. Panel (a) also shows that the gain from learning increases with α. This is because students with higher α have a higher chance of admission to college 1, making the acquisition of additional information more valuable. As a result, the threshold $\overline{\epsilon}(\alpha)$ increases with α.

We now turn to students' initial learning decisions—whether to learn ϵ_1. Let

$$V_1(\alpha) := \max\{U(\epsilon_1;\alpha) - c, U(\epsilon_1, \epsilon_2;\alpha) - 2c\}$$

denote the ex-ante expected payoff for a student with α from learning ϵ_1. The first term in the braces is the expected payoff from learning only ϵ_1, where $U(\epsilon_1;\alpha) := \mathbb{E}[u(\epsilon_1;\alpha)]$, and the second term is that from learning both ϵ_1 and ϵ_2, where $U(\epsilon_1, \epsilon_2;\alpha) := \mathbb{E}[u(\epsilon_2|\epsilon_1;\alpha)]$. A student chooses to learn ϵ_1 if and only if $V_1(\alpha)$ exceeds the ex-ante expected payoff from submitting $1 \succ 2$ without learning, $V_0(\alpha) := Q_2(\alpha)q_2 + Q_1(\alpha)\Delta$. As shown in panel (b) of Figure 1, there exists a $\overline{c}(\alpha)$ such that $V_1(\alpha) > V_0(\alpha)$ if and only if $c < \overline{c}(\alpha)$, or equivalently, $\alpha > \alpha^*$, where α^* satisfies $\overline{c}(\alpha^*) = c$. Thus, students with $\alpha \leq \alpha^*$ do not learn ϵ_1, while those with $\alpha > \alpha^*$ do, following the learning and ROL submission strategies described earlier. Panel (c) of Figure 1 summarizes these behaviors.

The analysis for the case where students learn ϵ_2 followed by ϵ_1 mirrors the previous case. A student learns ϵ_1 after observing ϵ_2 if $\epsilon_2 \in (-\overline{\epsilon}(\alpha) + \Delta, \overline{\epsilon}(\alpha) + \Delta)$, and learns ϵ_2 initially if $V_2(\alpha) > V_0(\alpha)$, where $V_2(\alpha)$ is defined analogously to $V_1(\alpha)$. Importantly, in Appendix A.1, we show that $V_1(\alpha) = V_2(\alpha)$ for all α, meaning that the learning order is irrelevant. To see why, note that when students learn only one ϵ_i, learning ϵ_1 can change the student's ranking if $\epsilon_1 < -\Delta$ (i.e, $q_1 + \epsilon_1 < q_2$), and learning ϵ_2 can change the ranking if $\epsilon_2 > \Delta$ (i.e., $q_1 < q_2 + \epsilon_2$). By the symmetry of G, $\text{Prob}(\epsilon_1 < -\Delta) = G(-\Delta) = 1 - G(\Delta) = \text{Prob}(\epsilon_2 > \Delta)$, so learning either ϵ_1 or ϵ_2 provides the same information about the colleges' expected values. Similarly, for a given ϵ_i, additional learning of ϵ_j matters only when it alters the rankings, and the order is irrelevant since $\epsilon_1 \gtrless \epsilon_2 - \Delta \Leftrightarrow q_1 + \epsilon_1 \gtrless q_2 + \epsilon_2 \Leftrightarrow \epsilon_2 \lessgtr \epsilon_1 + \Delta$.

The discussion so far is based on a given $(\hat{s}_1, \hat{s}_2)$. In the proof of Theorem 1, we show that the cutoff scores are endogenously determined so that the mass of students assigned to each college equals its capacity, and that no equilibrium satisfies $\hat{s}_1 \leq \hat{s}_2$.

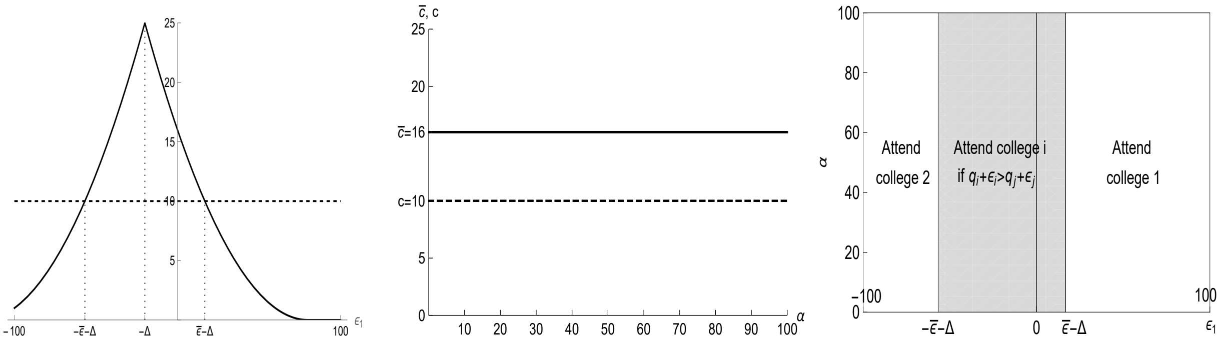
Remark 1. The irrelevance of learning order does not generally extend to settings with more than two colleges. To illustrate, consider three colleges with $q_1 > q_2 > q_3$ and $q_1 - q_2 = q_2 - q_3 \equiv \Delta$. Suppose that the learning cost is high enough that students can learn only one ϵ_i for $i = 1, 2, 3$. In this case, it is optimal to learn ϵ_2. Intuitively, learning ϵ_2 can yield the rank orders $1 \succ 2 \succ 3$ (if $q_1 > q_2 + \epsilon_2 > q_3$), $2 \succ 1 \succ 3$ (if $q_2 + \epsilon_2 > q_1 > q_3$), or $1 \succ 3 \succ 2$ (if $q_1 > q_3 > q_2 + \epsilon_2$). In contrast, learning ϵ_1 yields $1 \succ 2 \succ 3$ ($q_1 + \epsilon_1 > q_2 > q_3$), $2 \succ 1 \succ 3$ ($q_2 > q_1 + \epsilon_1 > q_3$), or $2 \succ 3 \succ 1$ ($q_2 > q_3 > q_1 + \epsilon_1$). While the first two rank orders arise with the same probability under both learning strategies, the third differs: the condition for $1 \succ 3 \succ 2$ (i.e., $\epsilon_2 < -\Delta$) is more likely than that for $2 \succ 3 \succ 1$ (i.e., $\epsilon_1 < -2\Delta$). Thus, learning ϵ_2 is more likely to revise the rank order and therefore yields a higher expected payoff than learning ϵ_1 (or likely ϵ_3). When students can learn multiple ϵ_i's at low cost, this suggests a sequential search problem with an endogenous learning order, which is beyond the scope of this paper.

Nevertheless, a tractable extension arises when colleges are ex-ante symmetric, $q_1 = q_2 = q_3 \equiv q$. In this case, the learning order is irrelevant and the learning decision resembles the two-college setting: a student with α learns any ϵ_i if $c < \bar{c}(\alpha)$ and proceeds to learn ϵ_j if $|\epsilon_i|$ is below a threshold, and so on. A key difference from the two-college case is that the expected gain from learning ϵ_j, after observing ϵ_i, depends on the sign of ϵ_i. If $\epsilon_i > 0$, the student compares colleges i and j, as college i's value, $q + \epsilon_i$, exceeds that of college k, q. If $\epsilon_i \leq 0$, she instead compares j and k, since college i now offers less than q. Aside from this, the structure of learning remains similar. See Appendix B for a formal analysis.

2.3 Benchmark Admissions System and Welfare Analysis

In this section, we study students' welfare. Formally, we define student welfare as

$$SW := (MV_1 + MV_2) - c\, m_L,$$



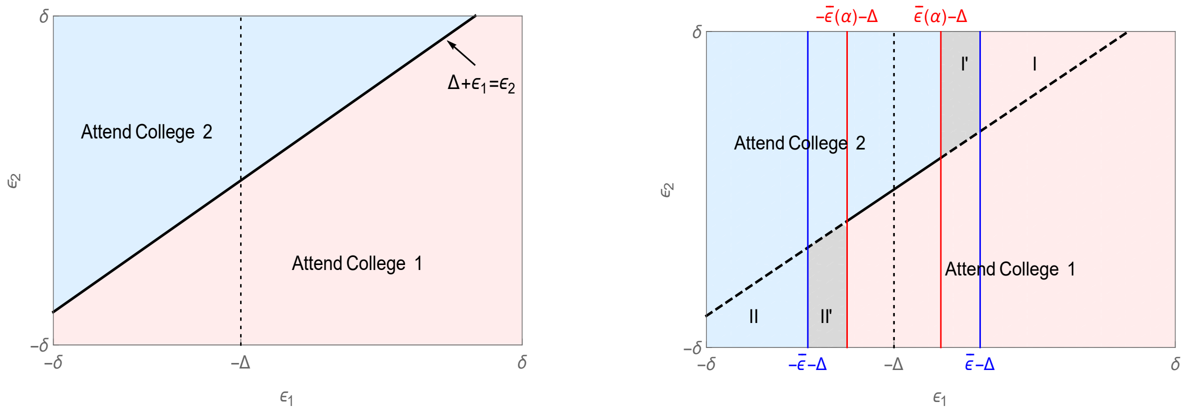
(a) Learning ϵ_2 after observing ϵ_1 (b) Learning decision for ϵ_1 (c) Enrollment decision

Figure 2: **Learning and enrollment decisions in the benchmark.** The parameters are the same as those in Figure 1. In equilibrium, $\bar{c} = 16$, $\bar{\epsilon} \simeq 36.57$, and $(\hat{s}_1, \hat{s}_2) \simeq (40, 30.98)$. The solid lines in panels (a) and (b) represent $u(\epsilon_2|\epsilon_1) - u(\epsilon_2)$ and $\bar{c}$, respectively, and the dashed line represents c. In panel (c), the gray region represents students who have learned $\epsilon_1 \in (-\bar{\epsilon} - \Delta, \bar{\epsilon} - \Delta)$.

where MV_i is the aggregate expected value of students attending college i (given the information they have), and m_L is the mass of students who learn at least one ϵ_i. Intuitively, the "match value" $MV_1 + MV_2$ increases as more students learn and are assigned to the college that has a higher value. Facing preference uncertainty, students have incentives to learn suitability since, by doing so, they can increase their expected value by reducing mis-assignment. Admission uncertainty, however, reduces incentives to learn since it lowers admission probabilities and thus the expected return to learning, thereby potentially reducing welfare.

To isolate the effect of admission uncertainty on welfare, we introduce a benchmark admissions system that preserves preference uncertainty but eliminates admission uncertainty by allowing students to make their learning decisions after admission outcomes are known. We then compare welfare under DA and the benchmark. In particular, our benchmark captures the welfare loss driven by preference uncertainty alone (i.e., the loss due to costly and incomplete learning when admission outcomes are known), while the additional gap between DA and the benchmark captures the welfare loss attributable to admission uncertainty.

Consider the following benchmark admissions process: at $t = 1$, students apply to colleges at no cost; at $t = 2$, colleges admit students based on their final scores; and at $t = 3$, students decide where to enroll. In this benchmark (a hypothetical decentralized admissions system), it is a weakly dominant strategy for students to apply to both colleges and delay learning until they have observed whether they are admitted by both colleges (but before making an enrollment decision). Since students' payoffs from attending colleges are independent of their exam scores, their learning decisions in this benchmark do not depend on α. Apart from this, the analysis is analogous to that of DA. Specifically, since $\hat{s}_1 > \hat{s}_2$, students with $s \geq \hat{s}_1$ are admitted by both colleges, those with $s \in [\hat{s}_2, \hat{s}_1)$ are admitted only to college 2, and the rest



(a) First-best allocation

(b) Allocation for a given α

Figure 3: Allocations for those with $s \geq \hat{s}_1$.

are rejected. Consequently, only the first group—those admitted to both—may benefit from learning, while the second group enrolls in college 2 without learning. For the first group, learning and enrollment decisions mirror those of DA, except that $Q_1(\alpha) = Q_2(\alpha) = 1$ since they are already admitted to both colleges. Figure 2 illustrates the equilibrium decisions in the benchmark using the same parameters as in Figure 1, assuming that students learn ϵ_1 first. Note that the thresholds $\bar{c}$ and $\bar{\epsilon}$ in Figure 2 correspond to $\bar{c}(\alpha)$ and $\bar{\epsilon}(\alpha)$ in DA evaluated at $Q_1(\alpha) = 1$. It follows immediately that $\bar{c}(\alpha) \leq \bar{c}$ and $\bar{\epsilon}(\alpha) \leq \bar{\epsilon}$ for all α.

We now use the benchmark to interpret the welfare consequences of the two sources of uncertainty. Assume that students, if they choose to learn, begin by learning ϵ_1 under both DA and the benchmark. They then proceed to learn ϵ_2 if $\epsilon_1 \in (-\bar{\epsilon}(\alpha) - \Delta, \bar{\epsilon}(\alpha) - \Delta)$ under DA and $\epsilon_1 \in (-\bar{\epsilon} - \Delta, \bar{\epsilon} - \Delta)$ under the benchmark. Since $\bar{\epsilon}(\alpha) \leq \bar{\epsilon}$, we have $(-\bar{\epsilon}(\alpha) - \Delta, \bar{\epsilon}(\alpha) - \Delta) \subseteq (-\bar{\epsilon} - \Delta, \bar{\epsilon} - \Delta)$, so conditional on learning ϵ_1, students are less likely to acquire additional information under DA. That is, DA yields a lower *intensive learning margin.* To understand its welfare implication, see Figure 3, which illustrates allocations of students with final scores exceeding $\hat{s}_1$. The left panel depicts the optimal allocation under full information: students are assigned to college 1 if $\epsilon_1 > \epsilon_2 - \Delta$ and to college 2 otherwise. The right panel shows allocations under the benchmark and DA. In the benchmark, students learn ϵ_2 only when $\epsilon_1 \in (-\bar{\epsilon} - \Delta, \bar{\epsilon} - \Delta)$, so those in region I (resp., II) attend college 1 (resp., 2), even though they would have preferred college 2 (resp., 1) if they had learned ϵ_2. This generates an efficiency loss due to preference uncertainty: even without admission uncertainty, mis-assignment is inevitable because learning is costly and therefore incomplete. Admission uncertainty amplifies this inefficiency under DA by further shrinking the range of realizations of ϵ_1 in which learning ϵ_2 is privately optimal. Precisely, since $\bar{\epsilon}(\alpha) \leq \bar{\epsilon}$, students in regions I′ and II′ also forgo learning ϵ_2 and are mis-assigned.

Turning to the *extensive learning margin*, recall that $\bar{c}(\alpha) \le \bar{c}$ for all α and $\bar{c}(\alpha^*) = c$. For any $c < \bar{c}$, students with $\alpha > \alpha^*$ under DA and those admitted by both colleges under the benchmark learn at least one ϵ_i. Since α^* is increasing in c, fewer students acquire information under DA as c rises, whereas it remains constant in the benchmark as long as $c < \bar{c}$. That is, admission uncertainty makes participation in learning more sensitive to learning cost. When c is high, DA yields both lower intensity and lower participation in learning, leading to lower welfare. When c is low, DA may exhibit a larger extensive margin, potentially raising welfare. However, in this case, although students with lower exam scores begin to learn, they are less likely to be assigned to their preferred colleges. Consequently, their learning has less welfare impact than that of students with higher exam scores, who are more likely to be assigned to their desired colleges and therefore have a greater impact on welfare.

Let superscripts D and B denote the equilibrium values under DA and the benchmark, respectively. The observations above yield the following results:

Theorem 2. *$SW^D < SW^B$ for any $r \in [0, 1)$, whereas $SW^D = SW^B$ at $r = 1$. Moreover, SW^B is invariant in r for any $\Delta \ge 0$, and SW^D increases in r whenever $\Delta = 0$.*

Proof. See Appendix A.2. ■

The welfare comparison of SW^D across different values of r is complicated. When $r = 1$, no students face admission uncertainty, and only those with sufficiently high exam scores acquire information. As r decreases, however, students with high exam scores become more likely to receive low final scores, reducing their admission chance to preferred colleges and so lowering the expected gain from learning. Conversely, those with low exam scores become more likely to receive high final scores, strengthening their incentives to learn. This asymmetry complicates theoretical predictions about the welfare effects of admission uncertainty.

A tractable case arises when $\Delta = 0$. In this case, we have $\hat{s}_1 = \hat{s}_2 \equiv \hat{s}$, so $Q_1(\alpha) = Q_2(\alpha) \equiv Q(\alpha)$. In the proof of Lemma A6 in Appendix A.2, we show that

$$\frac{dQ(\alpha)}{dr} = \frac{\alpha - \mathbb{E}[\alpha]}{2\eta(1-r)^2}.$$

This highlights the aforementioned asymmetry: as r decreases, students above the average exam score, $\mathbb{E}[\alpha]$, face a lower admission probability, while those below the average face a higher one. We further show that the sign of $\frac{dSW^D}{dr}$ coincides with that of

$$\int_{\alpha^*}^{\overline{\alpha}} \frac{dQ(\alpha)}{dr} dF(\alpha) = \frac{1 - F[\alpha^*]}{2\eta(1-r)^2} \big(\mathbb{E}[\alpha|\alpha \ge \alpha^*] - \mathbb{E}[\alpha]\big) \ge 0,$$

which implies that SW^D increases in r. Intuitively, changes in r affect $Q(\alpha)$ directly and also influence α^* (or $\bar{c}(\alpha)$) and $\bar{\epsilon}(\alpha)$ indirectly through $Q(\alpha)$. However, for small changes in r, the indirect effects are second-order: the marginal type α^* is indifferent between learning and not learning, and the marginal type who learns $\bar{\epsilon}(\alpha)$ is indifferent between learning one ϵ_i or two. As a result, the welfare change mainly comes from the direct effect of r on $Q(\alpha)$, leading to an increase in SW^D.

Although it is analytically intractable to derive such a result when $\Delta > 0$, a similar intuition would hold. Therefore, we experimentally consider an environment in which the monotonicity is preserved and empirically investigate the impact of the transparency using our experimental data.[9]

Remark 2. Given that real-life decentralized admissions often involve instability and congestion, one might consider alternative benchmarks. Hakimov, Kübler, and Pan (2023) study "sequential serial dictatorship," where students choose universities sequentially by priority order without submitting ROLs; in our setting, it yields the same outcome as our benchmark because students can decide whether to learn suitability when it is their turn to choose. Another relevant alternative is a "real-time" college-proposing DA, in which students respond in each round by accepting or rejecting an offer without submitting ROLs upfront. The DA mechanism used in Victoria, Australia, is of this kind: applicants submit ROLs before scores are released but may revise them after scores are released (Artemov, Che, and He, 2020). In our setting, such a system induces learning (and any ROL revision) only for students with final scores above $\hat{s}_1$, and therefore yields the same outcome as the benchmark.

While Theorem 2 highlights the informational inefficiency of DA, this does not necessarily imply that DA yields lower welfare than decentralized admissions. In our continuum model with no aggregate uncertainty, DA loses its advantages over the benchmark. With a finite number of students and endogenous effort choices, decentralized admissions may involve mixed application strategies (Hafalir et al., 2018), and DA eliminates colleges' enrollment uncertainty under aggregate preference uncertainty (Che and Koh, 2016). Nonetheless, our welfare analysis nests existing results: when $r = 0$, DA reduces to random serial dictatorship (RSD), and when $r = 1$, it becomes serial dictatorship; Theorem 2 therefore implies that RSD yields lower welfare than SD, consistent with Theorem 5 of Artemov (2021).

[9]We have numerically verified that under the parameters used in Figures 1 and 2 as well as the experiments, SW^D increases in $r \in [0, 1]$.

3 Experimental Design and Hypotheses

3.1 Experimental Design and Procedure

Our focus is on studying how different timings of information acquisition lead to different student welfare depending on the transparency of admission systems. To this end, we implement our experiment that features a 2×2 treatment design as presented in Table 1. The first treatment variable concerns the *transparency* of the admission system captured by $r \in [0, 1]$. $r = 1$ refers to the case of a fully transparent system, in which the single determinant of admissions is α, which is known to each student. $r = 0$ refers to the case of fully opaque system, in which the single determinant of admissions is θ, which is completely unknown to each student. We choose $r = 0.9$ and $r = 0.6$ for our treatment design.[10] The second treatment variable concerns whether the admission system is DA or the benchmark (BA). Treatments DH and DL (BH and BL) denote the DA (BA) system with high and low transparency, respectively. We refer to DH, DL and BH, BL as the DA and BA treatments, and to DH, BH and DL, BL as the high- and low-transparency treatments, respectively. The parameters and distributions chosen for our experiments are as follows: $\alpha \sim U[0, 100]$, $\theta \sim U[0, 100]$, $\epsilon_i \sim U[-100, 100]$, $c = 10$, $k = 0.4$, $\Delta = q_1 - q_2 = 170 - 150 = 20$, consistent with Figures 1 and 2, where the supports of the distributions are discretized to involve integer values only.

Table 1: Experimental treatments

		Transparency of Admission System	
		High ($r = 0.9$)	Low ($r = 0.6$)
Admission System	Deferred Acceptance (DA)	DH	DL
	Benchmark Admission (BA)	BH	BL

Our experiment was conducted using oTree (Chen, Schonger, and Wickens, 2016) at the HKUST via Zoom with the real-time online mode. Three sessions were conducted for each treatment. A total of 190 subjects were recruited from the graduate and undergraduate population of the university.[11] When invited, subjects were instructed to find a quiet place to stay for the entire duration of the experiment and join the designated Zoom meeting using their own laptop or desktop computer.[12] Turning on their video for the entire course

[10]The choice of r for our experimental design is guided by the fact that students in DA have no incentives to acquire information if r is too small (below 0.3 in our experimental environment). We thus chose a sufficiently large r to ensure that learning occurs in equilibrium.

[11]The number of participants was 49, 49, 47, and 45 for Treatments DH, BH, DL, and BL, respectively.

[12]We recommended they not use their mobile phone or tablet PC to join the experiment due to the

of the experiment was a strict requirement and chatting among subjects was prohibited by the Zoom settings. Each received an electronic copy of the experimental instructions via the chat message in Zoom. To ensure that the information contained in the instructions was public knowledge, the instructions were read aloud via Zoom. We used a between-subject design.

We illustrate the instructions for Treatment DH. The full experimental instructions for Treatment DH and Treatment BH are available in Appendices D.1 and D.2, respectively. There were two colleges, College 1 and College 2. The colleges were simple mechanical admission functions that admitted students as follows.[13] Upon receiving an application, each college admitted a student based on her exam scores (E) and interview scores (I) as well as an exogenously given admission cutoff. E and I were randomly and independently drawn according to the uniform distribution over $\{0, 1, 2, ..., 99, 100\}$ and correspond to α and θ for each student, respectively. Then, the exam score was announced to the student privately while the final score was sent to every college she applied to without being revealed to her.

Note that admission cutoffs are exogenously given by the theoretical predictions with capacity $k = 0.4$ for each college based on the model presented in the previous section with a continuum of students. It is as if an individual subject in our experiment cannot influence the admission decisions of the colleges and thus take the admission cutoffs as given. By doing so, we abstract away the colleges' strategic decisions. This approach allows us to focus on investigating students' learning decisions and their impact on the welfare generated by each admission system. Without colleges' strategic decisions, the remaining problem becomes a single-person decision problem for each student.

After the exam score (E) was revealed to each subject, she was asked to indicate her top choice between College 1 and College 2. Then the admission procedure began as follows:

1. The admission office sent the application to the college of her top choice.
2. The college accepted her application if her final score $T = 0.9 \times E + 0.1 \times I$ was higher than its own admission cutoff given as follows:

	DH	BH	DL	BL
$\hat{s}_1$	36.3	35	45.21	40
$\hat{s}_2$	23		30.98	

3. If her application was accepted by the college of her top choice, the admission process was finalized. Otherwise, the admission office sent her application to the college of her

potential concern of the presentation quality of the oTree game platform and of unexpected technical issues.

[13] As a result, participants in our experiments only played the role of students while the colleges were not strategic players making a deliberate choice.

second choice that decided whether to accept her application based on her final score T and the admission cutoff.

4. If her application was accepted by the college of her second choice, the admission process was finalized. Otherwise, she was not admitted by any college, and the process was finalized.

In case she received admission, she was asked to decide whether to pursue a college or not.

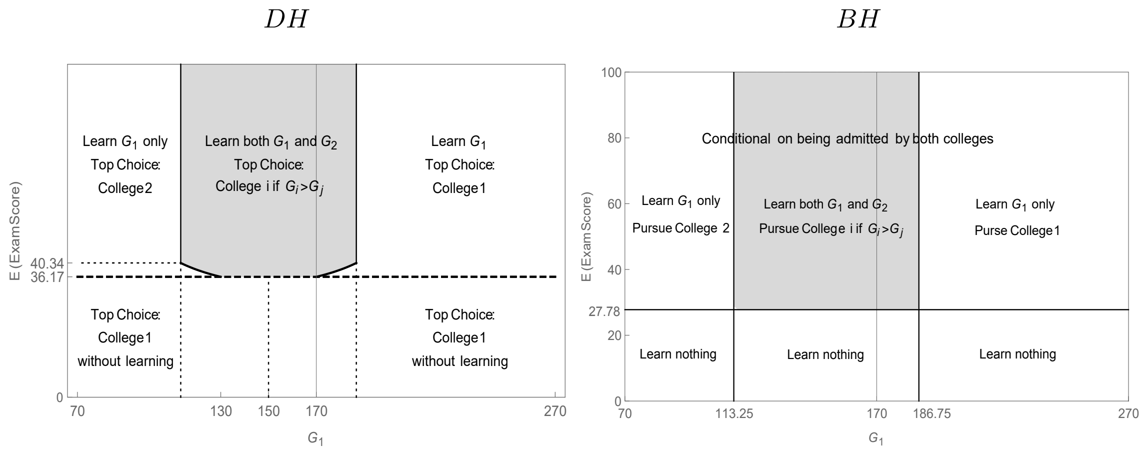
The gain a subject obtained from a college depended on how well the college suited her, corresponding to the value of college $q_i + \epsilon_i$ for each $i = 1, 2$. The gain (in tokens) from College 1, denoted by G_1, was randomly and independently chosen from {70, 71, 72, ..., 269, 270}, while each integer in the interval was equally likely. The gain from College 2, denoted by G_2, was randomly and independently chosen from {50, 51, 52, ..., 249, 250}, while each integer in the interval was equally likely. The gain became part of the earnings if and only if a college admitted the subject and the subject decided to pursue it.[14] Otherwise, a subject received the default gain of 50 tokens.

G_1 and G_2 were unknown to a subject at the beginning of each round. Once each round began, the decision screen for each subject contained two panels (left and right): one panel for the application decision and the other panel for the learning decision (see Figures D1 and D2 in Appendix D.1 for the screenshots). The placement (left or right) of the two panels was uniformly randomly chosen for each subject in each round. The learning panel allowed subjects to learn what the exact gain from College 1 (i.e., the value of G_1) was. If the subject decided to learn it, she needed to pay 10 tokens. Then, the subject further decided whether to learn what the exact gain from College 2 (i.e., the value of G_2) was.[15] If she decided to learn it, the subject needed to pay an additional 10 tokens. Note that the two panels were always presented side-by-side, and each panel ran independently from the other panel. Thus, it was entirely up to each subject 1) *whether* to learn none/one/both of G_1 and G_2 and 2) *when* to learn them. Subjects could learn none/one/both before or after they were admitted by a college or colleges. The learning cost did not depend on the timing of learning.

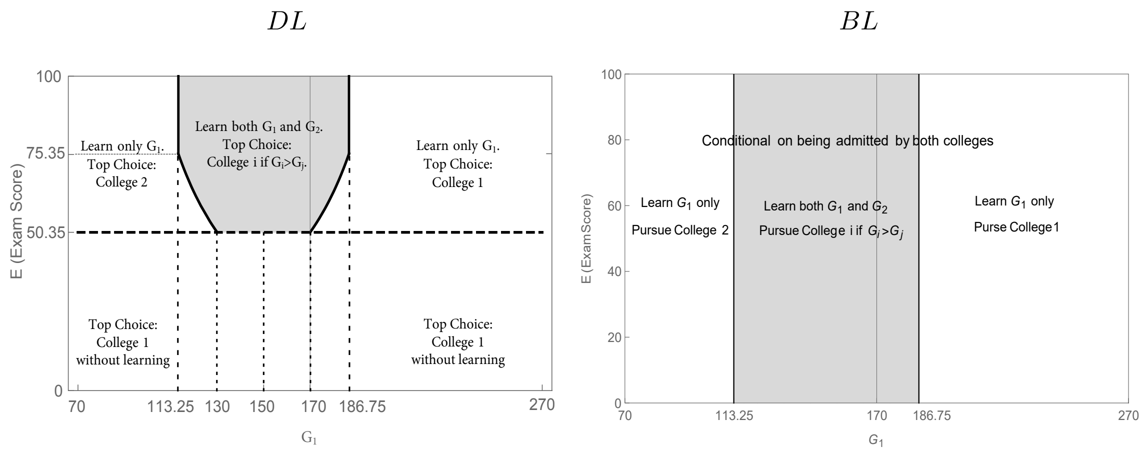
The earnings from each round were the gain from admission minus the total cost of

[14] While we assume that attending college is strictly more beneficial than not attending, our experimental design allowed subjects to choose whether or not to attend a college after being admitted. Some may argue that this design choice was unnecessary. However, research conducted by Narita (2018) using NYC high school matching data suggests that a significant proportion of students may not pursue their immediately available option due to various psychological reasons. Artemov, Che, and He (2020) and Shorrer and Sóvágó (2023) also document that a non-negligible fraction of Australian and Hungarian college applicants adopt unambiguously dominated strategies in strategically straightforward situations. Therefore, allowing subjects to choose whether or not to attend college may provide valuable insights into decision-making processes and the factors that influence them.

[15] We fixed the order of learning because it is not our primary objective to test the order-neutrality prediction.



(a) High transparency treatments



(b) Low transparency treatments

Figure 4: Outcome comparison

learning paid if a college admitted a subject and the subject decided to pursue it. Otherwise, it was the default 50 tokens minus the total cost of learning. At the end of each round, we provided feedback to each subject on her 1) exam score, 2) interview score, 3) final score, 4) which college(s) admitted her, 5) which college she pursued, 6) learning decisions, 7) G_1 and G_2 regardless of whether she paid to learn none/one/both of them, and 8) the earnings from the round. For the payment, one round out of the 30 rounds was randomly chosen. Including an HKD 40 show-up fee, subjects received, on average, HKD 190 (≈ USD 25). All payments were made electronically via the autopay system of HKUST to the bank account an individual participant provided to the Student Information System (SIS). Each session lasted approximately 1 hour on average.

3.2 Experimental Hypotheses

Figure 4 describes the outcomes from the theoretical predictions for the high- and low-transparency treatments, respectively, where the benchmark cases in both figures consider only those who are admitted by both colleges. The learning decisions, the top choice college in the case of DA and which college to pursue in the case of BA depend on two variables, G_1 (gains from College 1) presented on the horizontal axis and E (exam scores) presented on the vertical axis.

The key difference of DA relative to the benchmark admission system is the timing of learning. In the DA environment, students must learn before submitting their top-choice college, and there is no reason to learn further afterward. The BA offers different incentives to students. On one hand, according to the weakly undominated strategy equilibrium, students have incentives to learn only after they are admitted by both colleges. On the other hand, if the exam score is above 38.9 in BH and 66.7 in BL, students know that both colleges will admit them, regardless of the interview scores, so the timing of learning does not matter. Our first hypothesis summarizes this result.

Hypothesis 1 (**Timing of Learning $\mathbf{G_1}$**). *a) In Treatments DH and DL, students learn only before they submit their top choice college. b) In Treatments BH and BL, students whose exam scores are below 38.9 in BH and 66.7 in BL learn only after they are admitted by both colleges.*

The fact that students learn only after they are admitted by both colleges in the BA treatments implies that their first learning decision on G_1 must be independent of the exam score, as long as their exam scores are below 38.9 in BH and 66.7 in BL, which is demonstrated by the right panel of each of Figures 4(a) and 4(b). The area below $E = 27.78$ labeled as "Learn nothing" in the right panel of Figure 4(a) indicates that students whose exam score is below 27.78 cannot be admitted by both colleges regardless of their interview scores. However, in the DA treatments, the same learning decisions are crucially dependent upon the exam scores, as illustrated by the left panel of each of the two figures. We thus have our second hypothesis, as follows:

Hypothesis 2 (**$\boldsymbol{E}$-Dependence of $\mathbf{G_1}$ Learning**). *a) In treatments DH and DL, students learn G_1 only if the exam scores are above 36.17 in DH and 50.35 in DL. b) In treatments BH and BL, conditional on being admitted by both colleges, whether students learn G_1 does not depend on their exam scores.*

We now shift our attention to the G_2 learning decisions. *Among those who already learned G_1*, whether they *further* learn G_2 depends on the realization of G_1 in a specific way. As

Table 2: Social cost of pre-application learning

	MV_1	MV_2	TC	SW
DH	81.55	61.48	8.70	138.33
BH	82.30	65.85	9.12	139.03

Social cost of pre-application learning: 0.7

	MV_1	MV_2	TC	SW
DL	77.79	63.64	6.60	134.83
BL	82.30	65.85	9.12	139.03

Social cost of pre-application learning: 4.2

illustrated by Figure 4, the decisions are dependent upon whether the realized value of G_1 is in the range $[113.25, 186.75]$ in all four treatment conditions.[16] Thus, we have the following hypothesis.

Hypothesis 3 (**G_2 Learning**). *Among the students who already learned G_1, the proportion of students who further learn G_2 is substantially higher when the realized value of G_1 is in* $[113.25, 186.75]$ *in each treatment.*

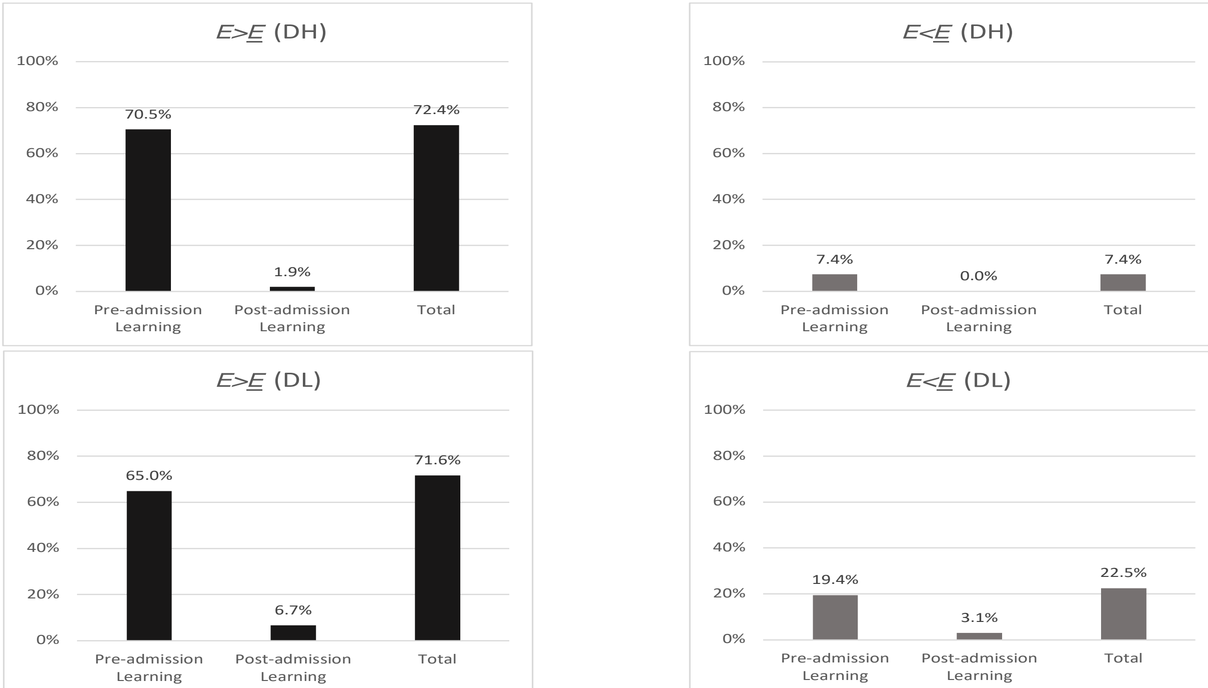
Our last hypothesis is about social welfare, our key prediction. Table 2 provides theoretical values of social welfare for each treatment. It illustrates that social welfare in DA is determined by the different learning decisions guided by different degrees of transparency. As a result, the **social cost of pre-application learning**, defined as the difference in social welfare between the two admission environments, is small (0.7) under the high transparency while that becomes substantially larger (4.2) under the low transparency. This result is summarized by our next hypothesis.

Hypothesis 4 (**Social Cost**). *The difference in the average social welfare between treatments DL and BL is substantially larger than that between treatments DH and BH.*

4 Experimental Results

We conduct our primary analysis using data aggregated over the last 20 rounds *for each individual*. All qualitative results are robust to the use of data from all 30 rounds or from the last 10 rounds. We begin in Section 4.1 by analyzing the G_1 learning decisions and then move to analyze the G_2 learning behavior. Section 4.2 presents the welfare analysis. In both G_1 and G_2 learning decisions, we identify non-equilibrium decisions, motivating us to have Section 4.3 that is devoted to investigating non-equilibrium decision-making and the welfare consequences. Appendix C presents four scatter diagrams (Figures C1 and C2) that

[16]Precisely speaking, this statement is not true because of the two triangular regions below the U-shaped gray areas in the left panels of Figures 4(a) and 4(b). However, we do not specify any testable hypothesis regarding those regions because it is unlikely for us to have sufficient observations that belong to those (small) regions in our data.



■ E refers to the exam score (that corresponds to α in the theoretical model). $\underline{E}$ = 36.17 in DH and $\underline{E}$ = 50.35 in DL.

Figure 5: Learning G_1 in treatments DH and DL

correspond to the theoretical counterparts presented in Figure 4, providing a general picture of the learning decisions observed in the laboratory, and several additional histograms for learning decisions.

4.1 Learning of G_1 and G_2

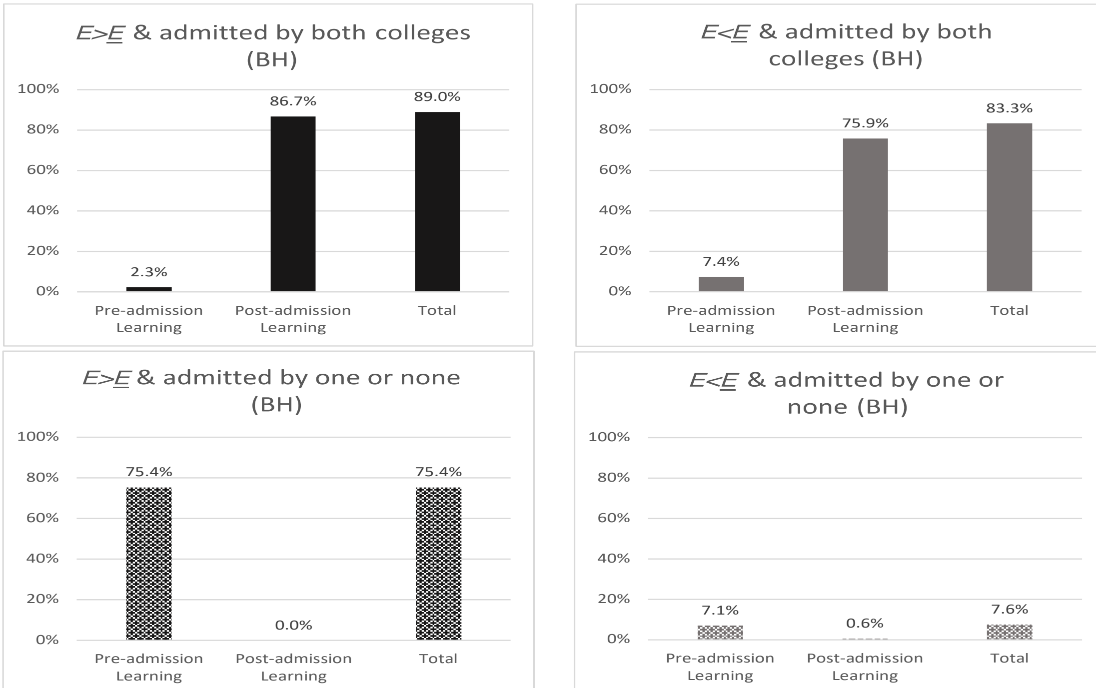
Figure 5 presents the G_1 learning (and timing of learning) decisions of students in treatments DH (two top panels) and DL (two bottom panels). When reporting the results, we divide observations into two categories. The left panels present the learning decisions made by students whose exam scores were above 36.17 in DH and 50.35 in DL: students in this category have incentives to learn before submitting their top choice college. The right panels present the learning decision made by the remaining students: theory predicts that they will not choose to learn anything at any time. To provide a more comprehensive understanding of the subjects' learning decisions, Figure C3 in Appendix C presents two histograms with a bin size of 10, separately for DH and DL. These histograms reaffirm our qualitative conclusion by showing that our findings are not contingent on the binary categories used in our main figures.

Three observations emerge. First, under-learning is observed in both DH and DL. The proportion of students who learned G_1 in the first category is slightly above 70% but below the theoretical prediction of 100%. Second, non-negligible proportions of those who have no incentives to learn decided to learn as reported in the right panels of Figure 5. In its magnitude, this observed *over-learning* is not as large as that of the *under-learning*. Third, if they learned, students almost always learned before submitting their top choice college. The last observation allows us to confirm Hypothesis 1(a).

Result 1 (Timing of learning $\mathbf{G_1}$ in DH and DL). *In treatments DH and DL, the vast majority of students learned G_1 before submitting their top choice colleges.*

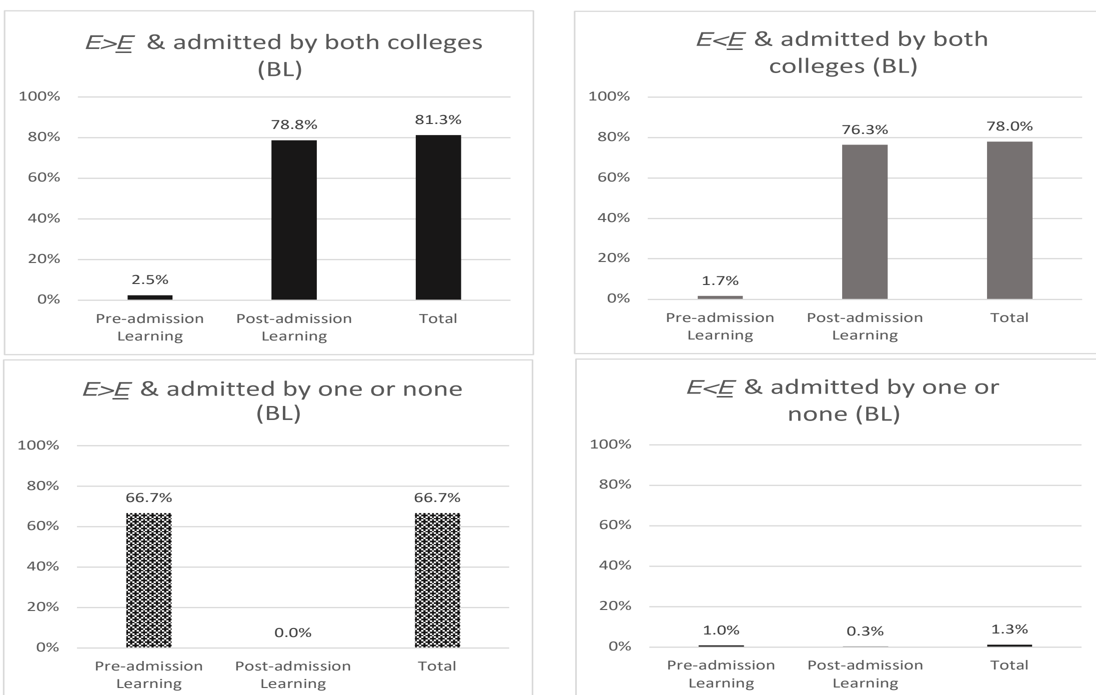
Figure 6 presents G_1 learning (and timing of learning) decisions of students in treatments BH and BL. Observations are divided into four categories. In each treatment, the top-left panel presents the learning decisions made by students whose exam scores were above 38.9 in BH and 66.7 in BL such that both colleges admitted them (regardless of the interview scores). The top-right panel presents the learning decisions made by those who had exam scores below 38.9 in BH and 66.7 in BL but were admitted by both colleges ex-post after the interview scores were realized. The bottom-left panel presents the learning decisions made by students whose exam scores were above 38.9 in BH and 66.7 in BL, so they were supposed to be admitted by both colleges, which did not happen due to the fact that they did not apply to both colleges. The bottom-right panel presents the learning decisions made by those who did not get admitted by both colleges with their exam scores below 38.9 in BH and 66.7 in BL. Figures C4 and C5 reported in Appendix C present two histograms each for the learning G_1 decision based on E with the bin size of 10 as well as whether being admitted by both colleges or not. These histograms provide further support for our qualitative conclusion, demonstrating that our findings remain consistent regardless of the binary categories employed in our primary figures.

A few observations are immediately clear in Figure 6. First, similar to the DA treatments, we observe under-learnings (relative to the equilibrium learning) in both BH and BL. Except for the fourth category, with exam scores below the cutoffs and without multiple admissions, students were supposed to learn G_1 100% of the time. The observed frequencies of learning G_1 are below 100%. Second, the left-bottom panels of Figures 6(a) and 6(b) report that students who received exam scores above 38.9 in BH and 66.7 in BL but did not apply to both colleges always learned G_1 before admission. Knowing that they would be admitted by both colleges, they learned which college suits them better even before admission and applied only to the better one. This behavior is optimal, even though we did not specify it in our theoretical analysis focusing on the weakly dominant strategies. Third, the two upper panels of Figures 6(a) and 6(b) indicate that vast majorities of students who applied to and



■ E refers to the exam score and $\underline{E}$ = 38.9.

(a) Treatment BH



■ E refers to the exam score E and $\underline{E}$ = 66.7.

(b) Treatment BL

Figure 6: Learning of G_1 in treatments BH and BL

were admitted by both colleges learned G_1 after they were admitted by both colleges. Last, students with exam scores below 38.9 in BH and 66.7 in BL who did not have multiple admissions rarely learned G_1. The last two observations allow us to confirm Hypothesis 1(b) as follows:

Result 2 (**Timing of learning $\mathbf{G_1}$ in BH and BL**). *The vast majority of students who applied to and were admitted by both colleges learned G_1 after being admitted by both colleges in both BH and BL. Without multiple admissions, the vast majority of students whose exam scores were below 38.9 in BH and 66.7 in BL did not learn G_1.*

Regarding Hypothesis 2(a), the positive proportions (7.4% and 22.5%) of learning observed in treatments DH and DL (the two right panels of Figure 5) from the students with exam scores below the cutoff values are not overwhelmingly large. Overall, the outcome is qualitatively consistent with the theoretical prediction because the vast majority of students who learned G_1 are those who had exam scores above the cutoffs. Comparison of the proportions of learning G_1 between students with exam scores above and below $\underline{E} = 38.9$ in treatment BH (89% vs. 83.3% on average) presented in the two top panels of Figure 6(a) enables us to confirm the first part of Hypothesis 2(b). These two values are not statistically different from each other (two-sided Wilcoxon test, p-value = 0.787). The same conclusion is drawn if we compare the proportions in treatment BL (81.3% vs. 78%) presented in the two upper panels of Figure 6(b). Again, these two values are not statistically different from each other (two-sided Wilcoxon test, p-value = 0.780). The following result summarizes these findings.

Result 3 (***E*-dependence of $\mathbf{G_1}$ learning**). *In treatments DH and DL, the vast majority of students who learned G_1 were those with exam scores above 36.17 in DH and 50.35 in DL. In treatments BH and BL, the G_1 learning decisions made by the students who were admitted by both colleges did not depend on their exam scores.*

Figure 7 presents the percentage of students who further learned G_2 given that they already learned G_1. Theory suggests that students who already learned G_1 have an incentive to learn G_2 only if G_1 is in the range of $[113.25, 186.75]$. The one-sided Wilcoxon test reveals that the percentage of students who further learned G_2 is significantly higher (p-values < 0.0001 for all four treatments) when G_1 is in $[113.25, 186.75]$ than when it is not. This observation allows us to confirm Hypothesis 3. However, suboptimal learning behaviors—both under-learning (i.e., the gray bars are below 100% in Figure 7) and over-learning (i.e., the dark and light blue bars are above 0% in Figure 7)—are observed across all treatments. Both types of suboptimal learning are substantial in magnitude. This observation motivates

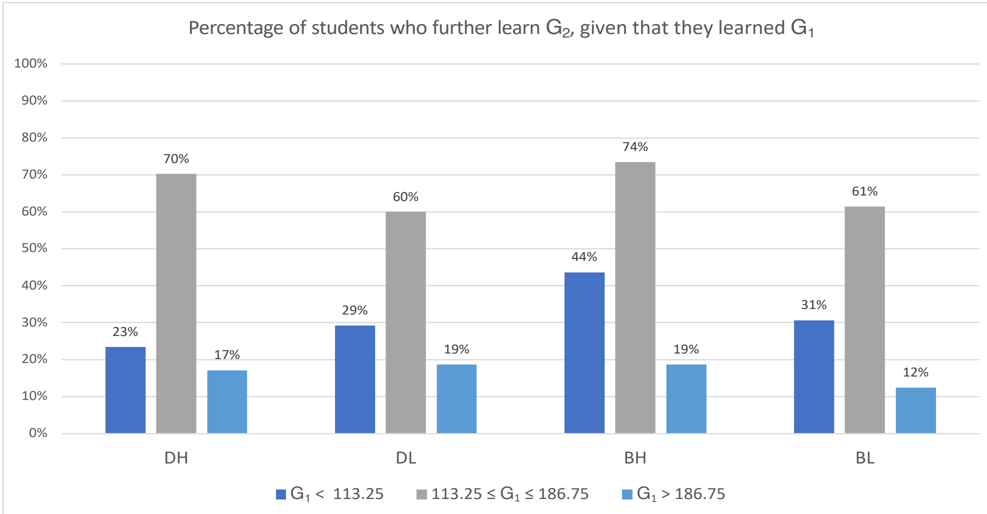


Figure 7: Learning G_2

us to look into the suboptimal decisions in more detail in Section 4.3. In Appendix C, two sets of histograms, labeled as Figure C6 and Figure C7, present a total of four histograms. These histograms showcase the learning decisions regarding G_2, categorized based on the realization of G_2, and are displayed with a bin size of 10 for each of the four treatments. These additional histograms contribute to the reinforcement of our qualitative conclusion, as they demonstrate the consistency of our findings irrespective of the binary categories used in our primary figures.

Result 4 ($\mathbf{G_2}$ learning). *Among the students who learned G_1, the proportion of students who further learned G_2 was substantially higher when the realized value of G_1 was in $[113.25, 186.75]$ in each treatment. However, a substantial degree of suboptimal learning was observed in all treatments.*

4.2 Welfare Analysis

Table 3 presents the ex-ante social welfare values that theory predicts based on the uniform prior of G_1 and G_2 (i.e., those presented in Table 2), as well as the ex-post social welfare values (presented in boldface) calculated based on the realizations of G_1 and G_2 according to our experimental data.[17] Given the large number of observations we have in our data, the ex-post social welfare values are reasonably close to the ex-ante values, and most of the ordinal welfare rankings are preserved, except that the social welfare value in DH (139.27)

[17] When calculating the ex-post social welfare values, we take the realization of G_1 and G_2 from our data and calculate the welfare based on the optimal strategy of the player.

Table 3: Theoretical Social Welfare

DH	MV_1	MV_2	TC	SW
Ex-ante	81.55	61.48	8.70	138.33
Ex-post	82.02	65.86	8.61	**139.27**
$\mathcal{R}$				0.94

DL	MV_1	MV_2	TC	SW
Ex-ante	77.79	63.64	6.60	134.83
Ex-post	77.47	65.79	6.30	**136.96**
$\mathcal{R}$				2.13

BH	MV_1	MV_2	TC	SW
Ex-ante	82.30	65.85	9.12	139.03
Ex-post	81.23	65.65	8.98	**137.90**
$\mathcal{R}$				-1.13

BL	MV_1	MV_2	TC	SW
Ex-ante	82.30	65.85	9.12	139.03
Ex-post	77.50	69.02	9.28	**137.25**
$\mathcal{R}$				-1.78

■ The ex-post social welfare values are calculated based on the optimal strategy of the player but by taking the realizations of G_1 and G_2 from our data (instead of the uniform prior).
■ When $G_1 = G_2$ and a student is admitted by both colleges, we assume that the student attends college 1 so that the corresponding matching value goes to college 1. There was one such tie case each in DH and BH.

Table 4: Empirical Social Welfare

	MV_1	MV_2	TC	SW
DH	81.56	61.32	6.70	136.18
BH	85.73	57.14	8.31	134.56

	MV_1	MV_2	TC	SW
DL	69.56	68.22	6.22	131.56
BL	75.34	65.66	7.08	133.92

■ The empirical social welfare values are calculated by adding the realized values of MV_1 and MV_2 across all subjects and then subtracting the total learning cost C paid.

is (marginally) larger than that in BH (137.90); apparently, the law of large numbers does not fully apply.

Table 4 presents the empirical social welfare values calculated using our data. Now we are ready to calculate the empirical social cost (SC) of pre-application learning as follows:

$$SC = \text{Adjusted Empirical Social Welfare in BA} - \text{Adjusted Empirical Social Welfare in DA},$$

where

$$\text{Adjusted Empirical Social Welfare} = \text{Empirical Social Welfare Value} - \mathcal{R}.$$

$\mathcal{R}$ =(Ex-post Social Welfare − Ex-ante Social Welfare) is a correction term to get rid of the effect of the different ex-post realizations of G_1 and G_2 across treatments. For example, the gap between the ex-post social welfare and the ex-ante social welfare in DH is $(139.27 - 138.33) = 0.94$ while that in BH is $(137.90 - 139.03) = -1.13$. Because both of them originate solely from the realizations of G_1 and G_2, we need to adjust the empirical social welfare by adding the correction term. Then the empirical social costs of pre-application learning for the high perfectness environment and the low perfectness environment are respectively

$$\begin{aligned} SC_H &= (134.56 + 1.13) - (136.18 - 0.94) = 0.45, \\ SC_L &= (133.92 + 1.78) - (131.56 - 2.13) = 6.27. \end{aligned}$$

Recall that the theoretical values for the social cost of pre-application learning provided in Table 2 are 0.7 and 4.2, respectively. The two-sided Mann-Whitney test confirms that the adjusted empirical social welfare in BH adjusted with the correction term is not different from the empirical social welfare in DH (p-value= 0.07314), implying that SC_H is not significantly different from 0. However, the same non-parametric test shows that the empirical social welfare in BL adjusted with the correction term is significantly different from the empirical social welfare in DL (p-value= 0.007593), implying that SC_L is significantly larger than 0. Another noticeable observation is that, in all treatments, the empirical social welfare values are strictly below the ex-post values presented in Table 3.[18] The empirical social welfare being strictly below the ex-post welfare is driven by the non-equilibrium learning decisions reported in the previous two subsections. This result also implies that the higher the transparency of admission system in DA the higher the empirical social welfare.

Result 5 (**Social Welfare**). *In all treatments, empirical social welfare values are strictly below the theoretical levels. The social cost of pre-application learning is significantly larger than zero in the low transparency environment but that is not the case in the high transparency environment.*

4.3 Non-equilibrium Learning and Welfare Decomposition

Where does the observed discrepancy between the empirical social welfare values and the theoretical ones come from? Apparently, the non-equilibrium learning identified in the previous subsections must be responsible. In this section, we thus investigate non-equilibrium learning more carefully and quantify the welfare loss (relative to the theoretical level) caused by different types of non-equilibrium decisions.

Non-equilibrium learning can be either over-learning or under-learning, where the former (the latter) implies that a student acquired more (less) information than the optimal amount prescribed by the equilibrium. Depending on whether the excessive (missing) learning is on G_1 only, G_2 only, or both, we categorize the non-equilibrium learning as over-learning (under-learning) G_1 only, G_2 only, or both. For example, “over-learning G_1 only” covers the cases

[18] The observed (individual-level) average welfare loss ranges between 3.09 and 5.40. These values are equivalent to 2.3%-7.4% of the empirical social welfare values and comparable to 40%-87% of the learning cost paid.

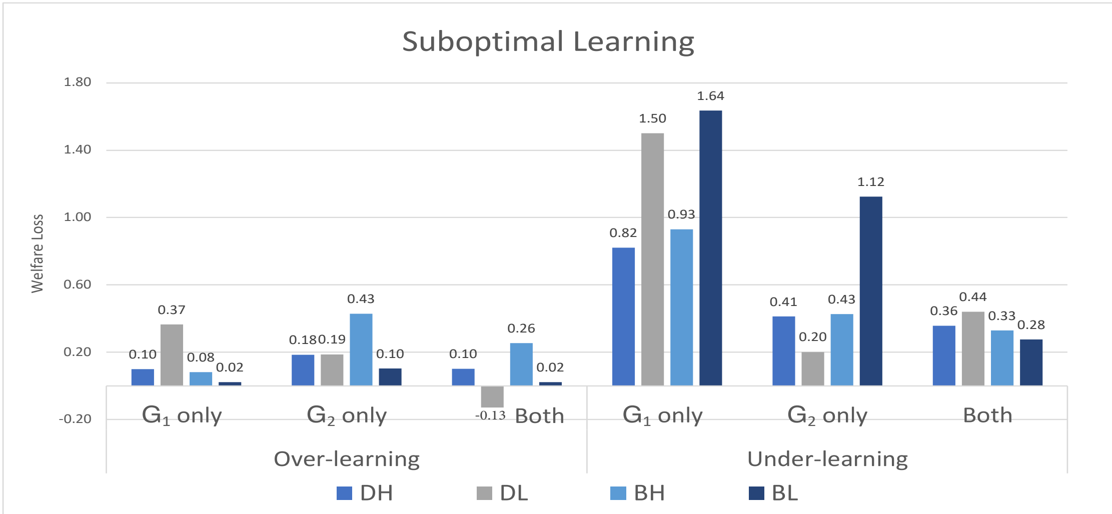


Figure 8: Decomposition of Welfare Loss from Suboptimal Learning

in which a student received an offer from one or no college but learned G_1 either in the pre-admission or in the post-admission stage.[19] For each observation classified as suboptimal learning, we calculate the welfare difference between the theoretical value (that the individual could have achieved if he/she were making the optimal learning decision) and the empirical value (coming from the suboptimal learning decision). The calculated welfare differences are aggregated for each category, and the results are reported in Figure 8.[20]

The decomposition of the welfare losses created by different types of suboptimal learning reported in Figure 8 leads to the following observations. First, in all treatments, under-learning was considerably more prevalent than over-learning. Second, among different types of under-learning, under-learning G_1 only was the greatest contributor to a welfare loss. Third, more suboptimal learning was observed in the low-transparency treatments (DL and BL) than in the high-transparency treatments (DH and BH). However, combining all welfare losses from suboptimal learning does not fully account for the observed welfare discrepancy presented in Table 4. For example, the welfare loss from all kinds of suboptimal learning in treatment DL was only 2.57 ($= 0.37 + 0.19 - 0.13 + 1.50 + 0.20 + 0.44$), which covers less than half of the total welfare loss (5.40). This observation implies that there must be

[19] "Over-learning G_2 only" covers the cases in which 1) a student received offers from both colleges, learned that G_1 is either below 113.25 or above 186.75, but decided to learn G_2 further, and 2) a student learned that G_1 is either below 113.25 or above 186.75 but learned G_2 further then applied to only one college. "Over-learning both" covers the cases in which the total score is below the admission cutoff of College 1 but at any point both G_1 and G_2 are learned. Under-learning is categorized and defined in a consistent manner.

[20] Both over-learning and under-learning could generate positive welfare gain ex-post. For example, in treatment DL, when the exam score is strictly below but sufficiently close to 50.35, the optimal decision is to choose College 1 as the top choice without learning. However, one could make a suboptimal decision to learn both G_1 and G_2. If $G_2 > G_1 + 20$ (the total learning cost paid) then suboptimal learning allows the decision-maker to submit the top choice of College 2 and get admitted, leading to a positive welfare gain.

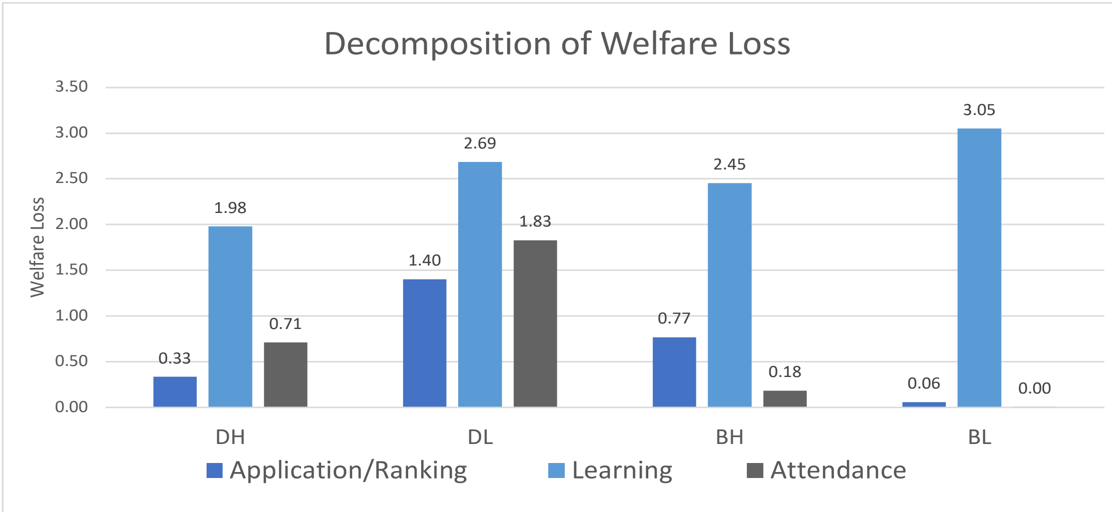


Figure 9: Decomposition of Welfare Loss from Non-equilibrium Decisions

other types of non-equilibrium decisions being made by our subjects.

Figure 9 reports the result from the decomposition of the welfare losses created by different types of suboptimal decisions that include not only suboptimal learning but also other types of mistakes. Clearly, suboptimal learning is the greatest contributor to the observed welfare loss, but it alone does not fully account for the entire amount. Two other kinds of suboptimal decisions are made in the ranking reporting (in DH and DL) / application (in BH and BL) decisions and attendance decisions. For example, mistakes in the ranking reporting in treatments DH and DL cover cases in which a student learned both G_i and G_j with $G_i > G_j$ but submitted the top choice college as j and the cases in which a student submitted the top choice college as the ex-ante worse one without learning. The application mistakes in treatments BH and BL cover cases in which a student applied only to College 2 even though he/she was supposed to be admitted by College 1 ex-post if he/she applied to College 1. The attendance mistakes cover cases in which one or more offers were made but a student did not pursue any college. This result is consistent with the empirical findings from the literature including Artemov, Che, and He (2023), Rees-Jones (2018) and Shorrer and Sóvágó (2023) that a non-negligible proportion of applicants in various matching contexts adopted dominated choices.

Result 6 (**Non-equilibrium Decisions**). *In all treatments, substantial degrees of non-equilibrium decisions are observed. Overall, non-equilibrium learning decisions are the greatest contributor to welfare loss.*

Notably, non-equilibrium *attendance* decisions are responsible for a large proportion of welfare loss in the DA treatments while (almost) no such mistakes are made in the BA treatments. To understand why this occurred only in the DA treatments, we first take a closer look at all 11 observations with attendance mistakes in treatment DL. In all but one case, the subjects chose College 1 (the ex-ante better college) as their top choice college without learning anything. With only one exception, the *post-admission learning* about both colleges or the college admitting the student occurred before the final rejection decision was made. This post-admission learning made students realize that they were admitted either by the college with a lower (than the other one) realized gain (8 cases) or by the college with a higher realized gain but the realized gain itself was not large (95 in one case and 111 in the other case) relative to the default gain of 50. The overall picture of the 5 cases involving attendance mistakes observed in treatment DH is exactly the same. All these observations suggest that the rejection decisions (attendance mistakes) are *associated with suboptimal post-admission learning* and may result from the disappointment students had when they learned they were admitted by the college with a relatively lower realized gain.

In Treatment DL, we also had mistakes in the ranking choice (top choice college) as another important contributor to the welfare loss, as indicated by the dark blue bar in Figure 9. The same kind of ranking choice mistakes was observed in treatment DH, but their welfare consequences were smaller (1.40 vs. 0.33). The observed suboptimal behavior is driven mainly by *pessimism*.[21] In treatment DL, 37 cases out of 39 in total occurred when students had no incentive to learn at all because their exam scores were below the cutoff 50.35.[22] Without learning, students in all 37 cases pessimistically chose College 2, the ex-ante inferior college, as their top choice. However, the final total scores were above the admission cutoff for College 1, so they would have been admitted to the ex-post better college if they had chosen College 1 as their top choice. In treatment DH, we had only 11 such cases, and the difference in their frequencies (39 in DL vs. 11 in DH) stemmed from the different degrees of transparency in these two treatments: students with low exam scores were more likely to be admitted by the college with a higher admission cutoff in treatment DL. As a result, pessimism led to a real mistake more often with lower transparency.

Do people learn to make fewer mistakes over time? Figure 10 presents the proportions of suboptimal decision-making. While the trend decreases over time across all treatments, the decline is modest except in two cases: the first 10 rounds in BL and the last 10 rounds in DL. In all cases, the proportions of suboptimal behavior remain above 25%, suggesting that learning occurs only to a limited extent. It is also evident that more frequent suboptimal

[21] The mistakes in the ranking choice observed in the DA treatments cannot be regarded as a behavior to distort the system and take strategic advantage over other students (see, e.g., Rees-Jones, 2017) because there are no strategic interactions among students in our environment.

[22] In the other 2 cases, students learned both G_1 and G_2 before submitting the topic choice, but they submitted the college with a lower realized value.

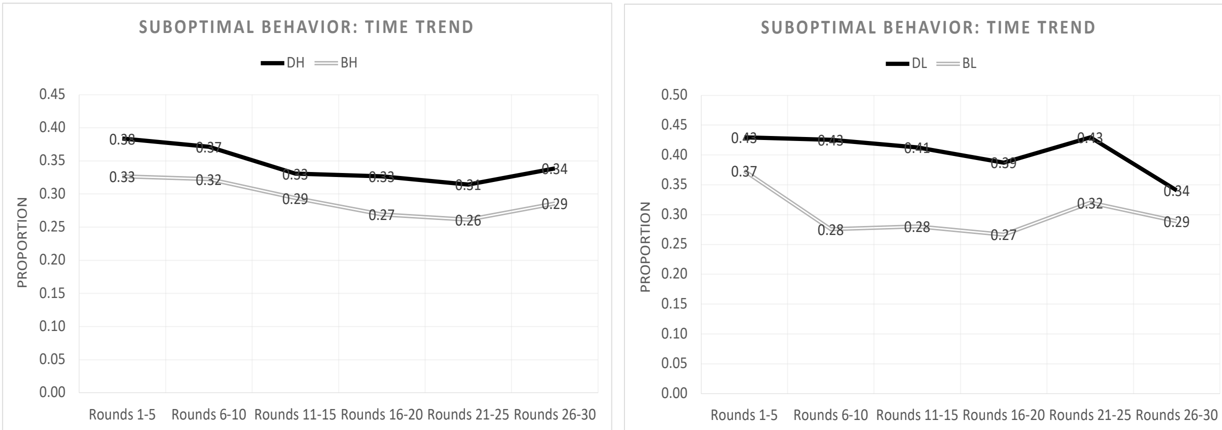


Figure 10: Welfare Loss - Time Trend

behaviors are observed in the DA treatments compared to the BA treatments, with a larger difference noted in the low transparency environment. This result explains why the empirical social cost of pre-application learning in our data is not as substantial as the theoretical value in general, and is even insignificantly different from zero in the low transparency environment.[23]

Why do people make non-equilibrium and thus suboptimal decisions? Although our experiment is not designed to address this question directly, we observe that subjects were more likely to make a suboptimal decision that led to a less substantial payoff loss. The average payoff losses from each suboptimal learning, ranking/application choice, and attendance decision are 8.9×10^{-3}, 79×10^{-3}, and 121×10^{-3}, while the corresponding treatment-average frequencies are 290, 13.75, and 4.5, respectively. This observation is in line with *payoff-dependent* mistakes, one of the most conventional ways to model mistake behavior in game theory, including Myerson (1978), Blume (1993), and McKelvey and Palfrey (1995).

5 Concluding Remarks

We theoretically and experimentally investigate the college admission system via DA when students' incentives to acquire information are influenced not only by the costs of obtaining information but also by the admission uncertainty that arises from the lack of full transparency in the admission system. In our theoretical analysis, we characterized students' learning and enrollment decisions and identified the efficiency loss of DA induced by pre-application learning relative to a benchmark system with post-admission learning. Consistent

[23] Figure C8 in Appendix C presents the time trend of the welfare loss. It indicates that the time trend of the welfare loss is more volatile in the high transparency environment than in the low transparency environment.

with our theory, we found in the laboratory that most students in DA acquired information only before submitting their top-choice colleges, while those in the benchmark acquired information after being admitted by both colleges. We also observed substantial degrees of suboptimal learning, as well as other suboptimal decisions, that contribute to the observed welfare loss.

A main contribution of our study is to empirically provide clear comparative statics results on how admission transparency influences students' incentives to acquire information. These results underscore the policy implication of transparent admission criteria and accessible information. When students can more accurately access their admission chances, they are more likely to acquire information on suitability and make choices that improve match efficiency. Conversely, opaque admission process both complicate decision-making and weaken incentives to seek information, thereby lowering overall welfare. Accordingly, policies that increase transparency—such as clearly describing the admissions process or providing guidance on how GPA translates into admission chances—can help students make better-informed choices, reduce the welfare costs of admission uncertainty, and improve efficiency in higher education matching markets.

Our findings also suggest that the degree of uncertainty students face during information acquisition should be an important consideration in the design of college admissions systems. Although it is not straightforward for the designer to induce a particular degree of uncertainty, it is not outright impossible either. For instance, Hakimov, Kübler, and Pan (2023) show in their experimental setting that providing historical cutoff scores in the direct serial dictatorship improves students' welfare. Similarly, Artemov (2021) proposes several policies, including the disclosure of priorities, that improve welfare when students' information acquisition matters in the random serial dictatorship. Although it is beyond the scope of this paper to design a particular mechanism, our analyses suggest that it is important to understand how the uncertainty that students face is translated into the informational (dis)advantage of different admission mechanisms.

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Online Appendix

In this appendix, we provide omitted proofs, discussions on more than two-college case, additional figures and tables, and sample instructions of the experiment.

A Omitted Proofs

A.1 Proof of Section 2.2

For given $\hat{s}_1 > \hat{s}_2$, we establish Lemmas A1 to A3 that characterize students' learning behaviors. We then show that $\hat{s}_1 > \hat{s}_2$ in equilibrium.

Lemma A1. *Suppose $\hat{s}_1 > \hat{s}_2$. For each α, the following results hold.*

(i) $u(\epsilon_j|\epsilon_i;\alpha) - u(\epsilon_j;\alpha) = 0$ if $\epsilon_1 \geq \delta - \Delta$ when $i = 1, j = 2$ or $\epsilon_2 \leq \Delta - \delta$ when $i = 2, j = 1$. Otherwise,

$$u(\epsilon_j|\epsilon_i;\alpha) - u(\epsilon_i) = Q_1(\alpha)\int_{|\epsilon_i+(j-i)\Delta|}^{\delta}(1 - G(\epsilon_j))d\epsilon_j,$$

which is strictly increasing (resp., decreasing) in ϵ_i for $\epsilon_i < (j-i)\Delta$ (resp., $\epsilon_i > (j-i)\Delta$). Moreover, $u(\epsilon_j|\epsilon_i;\alpha) - u(\epsilon_i;\alpha)$ is increasing in α.

(ii) For a given c, there exist $\bar{\epsilon}(\alpha)$ such that $u(\epsilon_j|\epsilon_i;\alpha) - u(\epsilon_j;\alpha) > c$ if $|\epsilon_i + (j-i)\Delta| < \bar{\epsilon}(\alpha)$, whenever $u(\epsilon_j|\epsilon_i;\alpha) - u(\epsilon_j;\alpha) > 0$. Moreover $\bar{\epsilon}(\alpha)$ is increasing in α.

Proof. (i). Suppose, first, that $i = 1$ and $j = 2$. Then, we have $u(\epsilon_1;\alpha) = Q_2(\alpha)q_2 + Q_1(\alpha)(\Delta + \epsilon_1)$ if $\epsilon_1 \geq -\Delta$ and $u(\epsilon_1;\alpha) = Q_2(\alpha)q_2$ if $\epsilon_1 < -\Delta$. Next, observe that

$$\begin{aligned}
u(\epsilon_2|\epsilon_1;\alpha) &= \int_{-\delta}^{\Delta+\epsilon_1}\left\{Q_1(\alpha)(q_1+\epsilon_1) + [(Q_2(\alpha) - Q_1(\alpha)](q_2+\epsilon_2)\right\}dG(\epsilon_2) \\
&\quad + \int_{\Delta+\epsilon_1}^{\delta} Q_2(\alpha)(q_2+\epsilon_2)dG(\epsilon_2) \\
&= Q_2(\alpha)q_2 + Q_1(\alpha)\int_{-\delta}^{\epsilon_1+\Delta}(\Delta+\epsilon_1-\epsilon_2)dG(\epsilon_j) \\
&= \begin{cases} Q_2(\alpha)q_2 + Q_1(\alpha)(\Delta+\epsilon_1) & \text{if } \epsilon_1 \geq \delta - \Delta, \\ Q_2(\alpha)q_2 + Q_1(\alpha)\int_{-(\Delta+\epsilon_1)}^{\delta}(1-G(\epsilon_2))d\epsilon_2 & \text{if } \epsilon_1 < \delta - \Delta, \end{cases}
\end{aligned} \tag{A.1}$$

where the last equality holds since for $\epsilon_1 \geq \delta - \Delta$,

$$\int_{-\delta}^{\epsilon_1+\Delta}(\Delta+\epsilon_1-\epsilon_2)dG(\epsilon_2) = \begin{cases} \int_{-\delta}^{\delta}(\Delta+\epsilon_1-\epsilon_2)dG(\epsilon_2) = \Delta+\epsilon_1 & \text{for } \epsilon_1 \geq \delta - \Delta, \\ \int_{-\delta}^{\epsilon_1+\Delta}G(\epsilon_2)d\epsilon_2 = \int_{-(\epsilon_1+\Delta)}^{\delta}(1-G(\epsilon_2))d\epsilon_2 & \text{for } \epsilon_1 < \delta - \Delta, \end{cases}$$

using the integration by parts and the symmetry of G for the case that $\epsilon_1 < \delta - \Delta$. Combining them together, we have that for $\Delta < \delta$,

$$u(\epsilon_2|\epsilon_1;\alpha) - u(\epsilon_1;\alpha) = \begin{cases} 0 & \text{if } \epsilon_1 \geq \delta - \Delta, \\ Q_1(\alpha)\left[-(\Delta+\epsilon_1) + \int_{-\epsilon_1+\Delta}^{\delta}(1-G(\epsilon_2))d\epsilon_2\right] & \text{if } \epsilon_1 \in [-\Delta, \delta-\Delta), \\ Q_1(\alpha)\int_{-(\Delta+\epsilon_1)}^{\delta}(1-G(\epsilon_2))d\epsilon_2 & \text{if } \epsilon_1 < -\Delta, \end{cases}$$

and for $\Delta \geq \delta$,

$$u(\epsilon_2|\epsilon_1;\alpha) - u(\epsilon_1;\alpha) = \begin{cases} 0 & \text{if } \epsilon_1 \geq \delta - \Delta, \\ Q_1(\alpha)\left[-(\Delta+\epsilon_1) + \int_{-(\epsilon_1+\Delta)}^{\delta}(1-G(\epsilon_2))d\epsilon_2\right] & \text{if } \epsilon_1 \in [-\delta, \delta-\Delta). \end{cases}$$

Thus, $u(\epsilon_2|\epsilon_1;\alpha) = u(\epsilon_1;\alpha)$ for $\epsilon_1 \geq \delta - \Delta$. Next, we establish the following result.

Claim A1. *For any* $\bar{\epsilon} \in [-\delta, \delta]$,

$$-\bar{\epsilon} + \int_{-\bar{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon = \int_{\bar{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon > 0.$$

Proof . For $\bar{\epsilon} \in [0, \delta]$, observe that

$$\begin{aligned} -\bar{\epsilon} + \int_{-\bar{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon &= -\bar{\epsilon} + \int_{-\bar{\epsilon}}^{0}(1-G(\epsilon))d\epsilon + \int_{0}^{\delta}(1-G(\epsilon))d\epsilon \\ &= -\int_{-\bar{\epsilon}}^{0}G(\epsilon)d\epsilon + \int_{0}^{\delta}(1-G(\epsilon))d\epsilon \\ &= -\int_{0}^{\bar{\epsilon}}(1-G(\epsilon))d\epsilon + \int_{0}^{\delta}(1-G(\epsilon))d\epsilon = \int_{\bar{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon > 0. \end{aligned}$$

The proof for the case with $\bar{\epsilon} \in [-\delta, 0)$ is similar, and we omit it. □

Note that for $\epsilon_1 < \delta - \Delta$, let $\bar{\epsilon} = \epsilon_1 + \Delta$. Then, the desired result follows from Claim A1. Next, consider the case that $i = 2$ and $j-1$. Then, it is easy to see that $u(\epsilon_2;\alpha)$ is $Q_2(\alpha)(q_2+\epsilon_2)$ if $\epsilon_2 > \Delta$ and is $Q_2(\alpha)(q_2+\epsilon_2) + Q_1(\alpha)(\Delta - \epsilon_2)$ if $\epsilon_2 \leq \Delta$. We also have that

$$\begin{aligned} u(\epsilon_1|\epsilon_2;\alpha) &= Q_2(\alpha)(q_2+\epsilon_2) + Q_1(\alpha)\int_{\epsilon_2-\Delta}^{\delta}(\Delta+\epsilon_1-\epsilon_2)dG(\epsilon_1) \\ &= \begin{cases} Q_2(\alpha)(q_2+\epsilon_2) + Q_1(\alpha)\int_{\epsilon_2-\Delta}^{\delta}(1-G(\epsilon_1))d\epsilon_1 & \text{if } \epsilon_2 > \Delta - \delta, \\ Q_2(\alpha)(q_2+\epsilon_2) + Q_1(\alpha)(\Delta-\epsilon_2) & \text{if } \epsilon_2 \leq \Delta - \delta. \end{cases} \end{aligned} \tag{A.2}$$

The remaining proof is analogous, and so we omit it.

(ii). Suppose $u(\epsilon_j|\epsilon_i;\alpha) - u(\epsilon_j;\alpha) > 0$. Define $\bar{\epsilon}(\alpha)$ such that

$$Q_1(\alpha)\int_{\bar{\epsilon}}^{\delta}(1 - G(\epsilon))d\epsilon = c.$$

Note that since $Q_1(\alpha)$ is increasing in α, so is $\bar{\epsilon}(\alpha)$. Otherwise, the left-hand side becomes smaller than c. ■

Lemma A2. *Suppose $\hat{s}_1 > \hat{s}_2$. For each α, the following results hold.*

(i) $U(\epsilon_i;\alpha) = U(\epsilon_j;\alpha) \geq V_0(\alpha)$, where the inequality is strict if $\Delta < \delta$.

(ii) $U(\epsilon_i,\epsilon_j;\alpha) = U(\epsilon_j,\epsilon_i;\alpha) > U(\epsilon_i;\alpha)$.

Proof. (i). From (2.2),

$$U(\epsilon_1;\alpha) = \int_{-\delta}^{\delta} u(\epsilon_1;\alpha)dG(\epsilon_1) = \begin{cases} Q_2(\alpha)q_2 + Q_1(\alpha)\int_{-\delta}^{\delta}(\Delta+\epsilon_1)dG(\epsilon_1) & \text{if } \Delta \geq \delta, \\ Q_2(\alpha)q_2 + Q_1(\alpha)\int_{-\Delta}^{\delta}(\Delta+\epsilon_1)dG(\epsilon_1) & \text{if } \Delta < \delta, \end{cases}$$

and similarly,

$$U(\epsilon_2;\alpha) = \int_{-\delta}^{\delta} u(\epsilon_2;\alpha)dG(\epsilon_2) = \begin{cases} Q_2(\alpha)q_2 + Q_1(\alpha)\int_{-\delta}^{\delta}(\Delta-\epsilon_2)dG(\epsilon_2) & \text{if } \Delta \geq \delta, \\ Q_2(\alpha)q_2 + Q_1(\alpha)\int_{-\delta}^{\Delta}(\Delta-\epsilon_2)dG(\epsilon_2) & \text{if } \Delta < \delta. \end{cases}$$

Hence, $U(\epsilon_1;\alpha) = U(\epsilon_2;\alpha) = Q_2(\alpha)q_2 + Q_1(\alpha)\Delta = V_0(\alpha)$ for $\Delta \geq \delta$. Suppose $\Delta < \delta$. Note that

$$\int_{-\delta}^{\Delta}(\Delta-\epsilon)dG(\epsilon) = \int_{-\delta}^{\Delta} G(\epsilon)d\epsilon = \int_{-\delta}^{\Delta}(1-G(-\epsilon))d\epsilon = \int_{-\Delta}^{\delta}(1-G(\epsilon))d\epsilon = \int_{-\Delta}^{\delta}(\Delta+\epsilon)dG(\epsilon),$$

hence, we have

$$\begin{aligned} U(\epsilon_1;\alpha) = U(\epsilon_2;\alpha) &= Q_2(\alpha)q_2 + Q_1(\alpha)\int_{-\Delta}^{\delta}(1-G(\epsilon))d\epsilon \\ &= Q_2(\alpha)q_2 + Q_1(\alpha)\left[\Delta + \int_{\Delta}^{\delta}(1-G(\epsilon))d\epsilon\right] = V_0(\alpha) + Q_1(\alpha)\int_{\Delta}^{\delta}(1-G(\epsilon))d\epsilon. \end{aligned} \tag{A.3}$$

(ii). Observe that $U(\epsilon_1,\epsilon_2;\alpha) = \int_{-\delta}^{\delta} u(\epsilon_2|\epsilon_1;\alpha)dG(\epsilon_1)$ and so from (A.1),

$$U(\epsilon_1,\epsilon_2;\alpha) = Q_2(\alpha)q_2 + Q_1(\alpha)\left[\int_{\delta-\Delta}^{\delta}(\Delta+\epsilon_1)dG(\epsilon_1) + \int_{-\delta}^{\delta-\Delta}\int_{-(\Delta+\epsilon_1)}^{\delta}(1-G(\epsilon_2))d\epsilon_2 dG(\epsilon_1)\right],$$

and similarly, $U(\epsilon_2,\epsilon_1;\alpha) = \int_{-\delta}^{\delta} u(\epsilon_1|\epsilon_2;\alpha)dG(\epsilon_2)$ and so from (A.2),

$$U(\epsilon_2,\epsilon_1;\alpha) = Q_2(\alpha)q_2 + Q_1(\alpha)\left[\int_{-\delta}^{\Delta-\delta}(\Delta-\epsilon_2)dG(\epsilon_2) + \int_{\Delta-\delta}^{\delta}\int_{-(\Delta-\epsilon_2)}^{\delta}(1-G(\epsilon_1))d\epsilon_1 dG(\epsilon_2)\right].$$

Note that

$$\int_{\delta-\Delta}^{\delta}(\Delta+\epsilon_1)dG(\epsilon_1)=\delta G(\Delta-\delta)+\int_{-\delta}^{\Delta-\delta}G(\epsilon)d\epsilon=\int_{-\delta}^{\Delta-\delta}(\Delta-\epsilon_2)dG(\epsilon_2),$$

using the integration by parts. Thus, the first terms in the square-bracket of $U(\epsilon_1,\epsilon_2;\alpha)$ and $U(\epsilon_2,\epsilon_1;\alpha)$ are identical. Next, observe also that

$$\begin{aligned}&\int_{-\delta}^{\delta-\Delta}\int_{-(\Delta+\epsilon_1)}^{\delta}(1-G(\epsilon_2))d\epsilon_2\,dG(\epsilon_1)=\int_{-\delta}^{\delta-\Delta}\int_{-(\Delta+\epsilon_1)}^{\delta}G(-\epsilon_2)d\epsilon_2\,dG(\epsilon_1)\\ =&\int_{-\delta}^{\delta-\Delta}\int_{-\delta}^{\Delta+\epsilon_1}G(t)dt\,dG(\epsilon_1)=\int_{\Delta-\delta}^{\delta}\int_{-\delta}^{\Delta-s}G(t)dt\,dG(s)\\ =&\int_{\Delta-\delta}^{\delta}\int_{-\delta}^{\Delta-s}(1-G(-t))dt\,dG(s)=\int_{\Delta-\delta}^{\delta}\int_{-\Delta+\epsilon_2}^{\delta}(1-G(\epsilon_1))d\epsilon_1\,dG(\epsilon_2).\end{aligned}$$

This shows that the last terms in the square-bracket of $U(\epsilon_1,\epsilon_2;\alpha)$ and $U(\epsilon_2,\epsilon_1;\alpha)$ are identical. Arranging terms yields that

$$U(\epsilon_1,\epsilon_2;\alpha)=U(\epsilon_2,\epsilon_1;\alpha)=V_0(\alpha)+Q_1(\alpha)\int_{-\delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon. \tag{A.4}$$

Thus, $U(\epsilon_i,\epsilon_j;\alpha)>U(\epsilon_i;\alpha)=V_0(\alpha)$ for $\Delta\geq\delta$. To see $U(\epsilon_i,\epsilon_j;\alpha)>U(\epsilon_i;\alpha)$ for $\Delta<\delta$, observe that from (A.3) and (A.4),

$$U(\epsilon_i,\epsilon_j;\alpha)-U(\epsilon_i;\alpha)=Q_1(\alpha)\left[\int_{-\delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon-\int_{\Delta}^{\delta}(1-G(\epsilon))d\epsilon\right] \tag{A.5}$$

$$\begin{aligned}&=Q_1(\alpha)\left[\int_{-\Delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon+\int_{-\delta}^{-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon-\int_{-\delta}^{-\Delta}G(\epsilon)d\epsilon\right]\\ &=Q_1(\alpha)\left[\int_{-\Delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon-\int_{-\delta}^{-\Delta}G(\Delta+\epsilon)G(\epsilon)d\epsilon\right]\\ &=Q_1(\alpha)\left[\int_{-\Delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon-\int_{-\delta}^{-\Delta}(1-G(-\Delta-\epsilon))(1-G(-\epsilon))d\epsilon\right]\\ &=Q_1(\alpha)\left[\int_{-\Delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon-\int_{0}^{\delta-\Delta}(1-G(t))(1-G(\Delta+t))dt\right]\\ &=Q_1(\alpha)\left[\int_{-\Delta}^{0}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon+\int_{0}^{\delta-\Delta}(1-G(\Delta+\epsilon))(2G(\epsilon)-1)d\epsilon\right]>0,\end{aligned}$$

where the fifth equality follows from change of variable ($t=-\Delta-\epsilon$), and the last equality holds since that $G(\epsilon)>\frac{1}{2}$ for any $\epsilon>0$ by the symmetry of G. ■

Lemma A3. *Suppose $\hat{s}_1>\hat{s}_2$. For each α, the following results hold.*

(i) There exists $\overline{c}(\alpha)$ such that $V(\alpha)>V_0(\alpha)$ whenever $c<\overline{c}(\alpha)$.

(ii) There exists α^* such that $c<\overline{c}(\alpha)$ if and only if $\alpha>\alpha^*$.

Proof. *(i).* Fix any α and suppose that $\Delta \geq \delta$. In this case, $U(\epsilon_i;\alpha) = V_0(\alpha)$ and from (A.4),

$$U(\epsilon_i,\epsilon_j;\alpha) - U(\epsilon_i;\alpha) = Q_1(\alpha)\int_{-\delta}^{\delta-\Delta}(1-G(\epsilon))d\epsilon =: \hat{c}(\alpha).$$

Therefore, if $c \geq \hat{c}(\alpha)$, $V(\alpha) = U(\epsilon_i;\alpha) - c < V_0(\alpha)$; and if $c < \hat{c}(\alpha)$, $V(\alpha) = U(\epsilon_i,\epsilon_j;\alpha) - 2c$. In the latter case, $V(\alpha) > V_0(\alpha)$ if and only if $c < \frac{\hat{c}(\alpha)}{2}$ from (A.4). Hence, we let $\overline{c}(\alpha) = \frac{\hat{c}(\alpha)}{2}$.

Next, suppose that $\Delta < \delta$. Define

$$\check{c}(\alpha) := U(\epsilon_i,\epsilon_j;\alpha) - U(\epsilon_i;\alpha) = Q_1(\alpha)\left[\int_{-\delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon - \int_{\Delta}^{\delta}(1-G(\epsilon))d\epsilon\right],$$
$$\tilde{c}(\alpha) := U(\epsilon_i;\alpha) - V_0(\alpha) = Q_1(\alpha)\int_{\Delta}^{\delta}(1-G(\epsilon))d\epsilon,$$

from (A.5) and (A.3), respectively. Note that $U(\epsilon_i,\epsilon_j) - 2c > U(\epsilon_i) - c$ if and only if $c < \check{c}(\alpha)$, and $u(\epsilon_i;\alpha) - c > V_0(\alpha)$ if and only if $c < \tilde{c}(\alpha)$. Next, let

$$W(\Delta;\alpha) := \check{c}(\alpha) - \tilde{c}(\alpha) = Q_1(\alpha)\left[\int_{-\delta}^{\delta-\Delta}(1-G(\Delta+\epsilon))G(\epsilon)d\epsilon - 2\int_{\Delta}^{\delta}(1-G(\epsilon))d\epsilon\right]$$

Observe that $W(\Delta;\alpha)$ is strictly increasing in Δ and $W(0;\alpha) < 0 < W(\delta;\alpha)$.[24] Hence, there exists a unique $\Delta^o \in (0,\delta)$ such that $W(\Delta^o;\alpha) = 0$.

- For $\Delta \in [\Delta^o, \delta)$, it holds that $\tilde{c}(\alpha) < \check{c}(\alpha)$. Note that for $c \geq \check{c}(\alpha)$, $U(\epsilon_i,\epsilon_j;a) - 2c \leq U(\epsilon_i;\alpha) - c \leq V_0$, where the last inequality holds since $U(\epsilon_i;\alpha) - c \leq V_0$ for $c \geq \tilde{c}(\alpha)$ and $\tilde{c}(\alpha) \leq \check{c}(\alpha) \leq c$. Thus, no student with α learns in this case. Next, for $c < \check{c}(\alpha)$, $U(\epsilon_i,\epsilon_j;a) - 2c > U(\epsilon_i;\alpha) - c$. In this case, $U(\epsilon_i,\epsilon_j;\alpha) - 2c > V_0(\alpha)$ if $c < \frac{\hat{c}(\alpha)}{2}$ and $U(\epsilon_i,;\alpha) - c > V_0(\alpha)$ if $c < \tilde{c}(\alpha)$. Hence, let $\overline{c}(\alpha) = \max\{\frac{\hat{c}(\alpha)}{2}, \tilde{c}(\alpha)\}$.
- For $\Delta < \Delta^0$, it holds that $\check{c}(\alpha) < \tilde{c}(\alpha)$. Note that for $c \geq \tilde{c}(\alpha)$, $U(\epsilon_i,\epsilon_j;\alpha) - 2c < U(\epsilon_i;\alpha) - c \leq V_0(\alpha)$, where the first inequality holds since $c > \check{c}(\alpha)$. Hence, no student learns. For $c < \tilde{c}(\alpha)$, $V(\alpha) \geq U(\epsilon_i;\alpha) - c > V_0(\alpha)$. Hence, we let $\overline{c}(\alpha) = \tilde{c}(\alpha)$.

In sum, $\overline{c}(\alpha)$ is given as follows:

$$\overline{c}(\alpha) := \begin{cases} \frac{\hat{c}(\alpha)}{2} & \text{for } \Delta \geq \delta, \\ \max\left\{\frac{\hat{c}(\alpha)}{2}, \tilde{c}(\alpha)\right\} & \text{for } \Delta^o \leq \Delta < \delta, \\ \tilde{c}(\alpha) & \text{for } \Delta < \Delta^o. \end{cases}$$

[24] $W(0) = Q_1(\alpha)\left[\int_{-\delta}^{\delta}(1-G(\epsilon))G(\epsilon)d\epsilon - 2\int_0^{\delta}(1-G(\epsilon))d\epsilon\right] = Q_1(\alpha)\left[2\int_0^{\delta}(1-G(\epsilon))G(\epsilon)d\epsilon - 2\int_0^{\delta}(1-G(\epsilon))d\epsilon\right] < 0$ by the symmetry of G, and $W(\delta;\alpha) = Q_1(\alpha)\int_{-\delta}^{0}(1-G(\delta+\epsilon))G(\epsilon)d\epsilon > 0$.

(ii). Note that since $Q_1(\alpha)$ is increasing in α, so are $\check{c}(\alpha)$ and $\tilde{c}(\alpha)$, further implying that $\overline{c}(\alpha)$ is increasing in α. For a given c, let $\alpha^* := \inf\{\alpha | \overline{c}(\alpha) \geq c\}$. It is clear that α^* is increasing in c and $c < \overline{c}(\alpha)$ if and only if $\alpha > \alpha^*$. ■

Lemmas A1 to A3 so far are based on fixed $\hat{s}_1 > \hat{s}_2$. In equilibrium, $(\hat{s}_1, \hat{s}_2)$ must be chosen to make the mass of students assigned to each college equal to its capacity k. We now show that there is a unique equilibrium in which $\hat{s}_1 > \hat{s}_2$.

Proof of Theorem 1. Let $\mathfrak{m}_i$ denote the mass of students assigned to each college i. Assuming that all students with $\alpha > \alpha^*$ learn ϵ_1 first, $\mathfrak{m}_1$ and $\mathfrak{m}_2$ are given as follows:

$$\mathfrak{m}_1 = \int_{\underline{\alpha}}^{\alpha^*} Q_1(\alpha) dF(\alpha) + m_{12} \quad \text{and} \quad \mathfrak{m}_2 = \int_{\underline{\alpha}}^{\overline{\alpha}} [Q_2(\alpha) - Q_1(\alpha)] dF(\alpha) + m_{21}, \tag{A.6}$$

where

$$m_{12} \equiv \int_{\alpha^*}^{\overline{\alpha}} Q_1(\alpha) \Big[\text{Prob}(\epsilon_1 \geq \overline{\epsilon}(\alpha) - \Delta) + \text{Prob}(|\epsilon_1 + \Delta| < \overline{\epsilon}(\alpha), \epsilon_2 \leq \epsilon_1 + \Delta) \Big] dF(\alpha),$$
$$m_{21} \equiv \int_{\alpha^*}^{\overline{\alpha}} Q_1(\alpha) \Big[\text{Prob}(\epsilon_1 \leq -\overline{\epsilon}(\alpha) - \Delta) + \text{Prob}(|\epsilon_1 + \Delta| < \overline{\epsilon}(\alpha), \epsilon_2 > \epsilon_1 + \Delta) \Big] dF(\alpha).$$

In what follows, we first show that there is a unique pair $(\hat{s}_1, \hat{s}_2)$ satisfying $\mathfrak{m}_1 = k = \mathfrak{m}_2$, and then show that such a pair must satisfy $\hat{s}_1 > \hat{s}_2$. The proof consists of several steps.

Step 1. *For any given* $(\hat{s}_1, \hat{s}_2)$, $m_{12} > m_{21}$

Proof . For any α, let $\overline{Q}(\alpha) \equiv \text{Prob}(s \geq \hat{s}_1, s \geq \hat{s}_2 | \alpha)$. Rewrite m_{12} and m_{21} as follows:

$$m_{12} = \int_{\alpha^*}^{\overline{\alpha}} \overline{Q}(\alpha) \left[(1 - G(\overline{\epsilon}(\alpha) - \Delta)) + \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta} G(\epsilon_1 + \Delta) dG(\epsilon_1) \right] dF(\alpha), \tag{A.7}$$

$$m_{21} = \int_{\alpha^*}^{\overline{\alpha}} \overline{Q}(\alpha) \left[G(-\overline{\epsilon}(\alpha) - \Delta) + \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta} (1 - G(\epsilon_1 + \Delta)) dG(\epsilon_1) \right] dF(\alpha). \tag{A.8}$$

Observe that for any given α, $1 - G(\overline{\epsilon}(\alpha) - \Delta) = G(-\overline{\epsilon}(\alpha) + \Delta) > G(-\overline{\epsilon}(\alpha) - \Delta)$ and

$$\begin{aligned} \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta} (1 - G(\epsilon_1 + \Delta)) dG(\epsilon_1) &= \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta} G(-\epsilon_1 - \Delta) dG(\epsilon_1) \\ &= \int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} G(t) dG(t) = \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta} G(\epsilon_1 + \Delta) dG(\epsilon). \end{aligned}$$

Thus, we have $m_{12} > m_{21}$. □

Step 2. $\hat{s}_1 > \hat{s}_2$.

Proof . Suppose $\hat{s}_1 = \hat{s}_2$. Then, $Q_1(\alpha) = Q_2(\alpha)$, so $\mathfrak{m}_1 = \int_{\underline{\alpha}}^{\alpha^*} Q_1(\alpha)dF(\alpha) + m_{12} > \mathfrak{m}_2 = m_{21}$, a contradiction. Next, suppose $\hat{s}_1 < \hat{s}_2$. Then, we have

$$\mathfrak{m}_1 = \int_{\underline{\alpha}}^{\alpha^*} Q_1(\alpha)dF(\alpha) + m_{12} > m_{21} > \mathfrak{m}_2 = \int_{\underline{\alpha}}^{\alpha^*} (Q_2(\alpha) - Q_1(\alpha))dF(\alpha) + m_{21},$$

where the second equality holds since $Q_2(\alpha) < Q_1(\alpha)$ for each α due to that $\hat{s}_1 < \hat{s}_2$, yielding a contradiction, again. Thus, we must have $\hat{s}_1 > \hat{s}_2$. □

Step 3. *There is a unique pair* $(\hat{s}_1, \hat{s}_2)$ *such that* $\mathfrak{m}_1 = k = \mathfrak{m}_2$.

Proof . First, note that since $s = r\alpha + (1-r)\theta$, $\alpha \in [\underline{\alpha}, \overline{\alpha}]$ and $\theta \in [-\eta, \eta]$, we have $s \in [\underline{s}, \overline{s}]$ where $\underline{s} \equiv r\underline{\alpha} - (1-r)\eta < \overline{s} \equiv r\overline{\alpha} + (1-r)\eta$. Consider $\mathfrak{m}_1$. Since $Q_1(\alpha)$ is decreasing in $\hat{s}_1$ and so is $\mathfrak{m}_1$. Moreover, $\hat{s}_1 < \overline{s}$ since otherwise $Q_1(\alpha) = 0$ for all α and so $\mathfrak{m}_1 = 0$, and $\hat{s}_1 > \underline{s}$ since otherwise $Q_1(\alpha) = 1$ for all α and so $\hat{s}_1 = \underline{s}_1 \le \hat{s}_2$, a contradiction to Step 2. Since $Q_1(\alpha)$ is strictly decreasing in $\hat{s}_1$ for $\hat{s}_1 \in (\underline{s}, \overline{s})$, it follows that there is a unique $\hat{s}_1$ satisfying $\mathfrak{m}_1 = k$.

Next, consider $\mathfrak{m}_2$. Observe that for the fixed $\hat{s}_1$ defined above, it is clear that $\hat{s}_2 \in (\underline{s}, \hat{s}_1)$. Note also that if $\hat{s}_2 \le \underline{s}$, then $\mathfrak{m}_2 = 1 - \mathfrak{m}_1 = 1 - k > k$, where the last equality follows from the definition of $\hat{s}_1$ and the inequality holds since $k < \frac{1}{2}$. Similarly, if $\hat{s}_2 \ge \hat{s}_1$, then $\mathfrak{m}_2 \le m_{21} < m_{12} < \mathfrak{m}_1 = k$, where the first inequality holds since $Q_2(\alpha) \le Q_1(\alpha)$, and the second inequality follows from Step 1. Since $\mathfrak{m}_2$ is strictly decreasing in $\hat{s}_2$ for $\hat{s}_2 \in (\underline{s}, \hat{s}_1)$, the desired result follows. □

Step 4. *There is no equilibrium with* $\hat{s}_1 \le \hat{s}_2$.

Proof . Suppose to the contrary that there is such an equilibrium. Observe that in this case, students with $s \ge \hat{s}_2$ will be assigned to whichever college they rank first in their ROL, and those with $s \in [\hat{s}_1, \hat{s}_2)$ (if $\hat{s}_1 < \hat{s}_2$) are assigned to college 1 regardless of their ROLs. A straightforward analysis yields that

$$u(\epsilon_i; \alpha) = Q_1(\alpha)\mathbb{E}[v_1|I] + Q_2(\alpha)(\mathbb{E}[v_2|I] - \mathbb{E}[v_1|I])\mathbf{1}_A,$$

where $\mathbb{E}[v_1|I] = q_1 + \epsilon_1$, $\mathbb{E}[v_2|I] = q_2$ and $A = \{\epsilon_1|\epsilon_1 < -\Delta\}$ if $\sigma(\alpha) = (1, \emptyset)$; or $\mathbb{E}[v_1|I] = q_1$, $\mathbb{E}[v_2|I] = q_2 + \epsilon_2$ and $A = \{\epsilon_2|\epsilon_2 > \Delta\}$ if $\sigma(\alpha) = (2, \emptyset)$. Similarly,

$$u(\epsilon_j|\epsilon_i; \alpha) = Q_1(\alpha)\mathbb{E}[v_1|I] + Q_2(\alpha) \int_A (-\Delta + \epsilon_2 - \epsilon_1)dG(\epsilon_{\sigma_2}),$$

where $\mathbb{E}[v_1|I] = q_1 + \epsilon_1$ and $A = \{\epsilon_2|\epsilon_2 > \epsilon_1 + \Delta\}$ if $i = 1$, $j = 2$; or $\mathbb{E}[v_1] = q_1$ and $A = \{\epsilon_1|\epsilon_1 < \epsilon_2 - \Delta\}$ if $i = 2$, $j = 1$. Using them, it is easy to see that for any ϵ_1,

$$u(\epsilon_2|\epsilon_1; \alpha) - u(\epsilon_1; \alpha) = Q_2(\alpha) \int_{|\epsilon_1 + \Delta|}^{\delta} (1 - G(\epsilon_2))d\epsilon_2,$$

since $u(\epsilon_1;\alpha) = Q_1(\alpha)(q_1+\epsilon_1)$ if $\epsilon_1 \geq -\Delta$; or $u(\epsilon_1;\alpha) = Q_1(\alpha)(q_1+\epsilon_1) + Q_2(\alpha)(-\epsilon_1-\Delta)$ if $\epsilon_1 < -\delta$, and

$$u(\epsilon_2|\epsilon_1;\alpha) = Q_1(\alpha)(q_1+\epsilon_1) + Q_2(\alpha)\int_{\epsilon_1+\Delta}^{\delta}(1-G(\epsilon_2))d\epsilon_2.$$

Similarly, we also have that for any ϵ_2,

$$u(\epsilon_1|\epsilon_2;\alpha) - u(\epsilon_2;a) = Q_2(\alpha)\int_{|\epsilon_2-\Delta|}^{\delta}(1-G(\epsilon_2))d\epsilon_2.$$

Therefore, the results from Lemmas A1 to A3 follow (with $V_0(\alpha) = Q_1(\alpha)q_1 - Q_2(\alpha)\Delta$), which in turn imply that

$$m_{12} = \int_{\alpha^*}^{\overline{\alpha}} Q_2(\alpha)\Big[\text{Prob}(\epsilon_1 \geq \overline{\epsilon}(\alpha)-\Delta) + \text{Prob}(|\epsilon_1+\Delta| < \overline{\epsilon}(\alpha), \epsilon_2 \leq \epsilon_1+\Delta)\Big]dF(\alpha)$$
$$m_{21} = \int_{\alpha^*}^{\overline{\alpha}} Q_2(\alpha)\Big[\text{Prob}(\epsilon_1 \leq -\overline{\epsilon}(\alpha)-\Delta) + \text{Prob}(|\epsilon_1+\Delta| < \overline{\epsilon}(\alpha), \epsilon_2 > \epsilon_1+\Delta)\Big]dF(a),$$

assuming that all students with $\alpha \geq \alpha^*$ learn ϵ_1 first. Note that m_{ij} captures the mass of students who submit ROL $i \succ j$ among those with $\alpha \geq \alpha^*$. Thus, the mass of students assigned to each college $i = 1, 2$ is given by

$$\mathfrak{m}_1 = \int_{\underline{\alpha}}^{\alpha^*} Q_1(\alpha)dF(\alpha) + \int_{\alpha^*}^{\overline{\alpha}}(Q_1(\alpha)-Q_2(\alpha))dF(\alpha) + m_{12} \quad \text{and} \quad \mathfrak{m}_2 = m_{21},$$

where the first term in the RHS of $\mathfrak{m}_1$ is the mass of students who submit ROL $1 \succ 2$ without learning the suits (since $q_1 > q_2$) among those assigned to college 1, and the second term those with $s \in [\hat{s}_1, \hat{s}_2)$ and so assigned to college 1 regardless of their ROLs. Note that $m_{12} > m_{21}$ by the same argument in Step 1, which implies that $\mathfrak{m}_1 > \mathfrak{m}_2$, a contradiction. □

A.2 Proof of Theorem 2

Consider the benchmark first and suppose that all students with $s \geq \hat{s}_1^D$ learn ϵ_1 first whenever $c < \overline{c}$. Then, $SW^B = MV^B - TC^B$. Note that $MV^B = MV_1^B + MV_2^B$ and

$$MV_1^B = \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\left[\int_{\overline{\epsilon}-\Delta}^{\delta}(q_1+\epsilon_1)dG(\epsilon_1) + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta}(q_1+\epsilon_1)dG(\epsilon_2)\right)dG(\epsilon_1)\right]dF(\alpha),$$
$$MV_2^B = \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\left[\int_{-\delta}^{-\overline{\epsilon}-\Delta} q_2 dG(\epsilon_1) + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{\epsilon_1+\Delta}^{\delta}(q_2+\epsilon_2)dG(\epsilon_2)\right)dG(\epsilon_1)\right]dF(\alpha)$$
$$+ \int_{\underline{\alpha}}^{\overline{\alpha}} q_2(Q_2^B(\alpha) - Q_1^B(\alpha))dF(\alpha).$$

Thus, we have

$$MV^B = \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\Big[\int_{\bar{\epsilon}-\Delta}^{\delta} (\Delta+\epsilon_1) dG(\epsilon_1) + \int_{-\delta}^{\bar{\epsilon}-\Delta} (q_2 - q_2) dG(\epsilon_1) \\ + \int_{-\bar{\epsilon}-\Delta}^{\bar{\epsilon}-\Delta} \Big(\int_{-\delta}^{\epsilon_1+\Delta} (\Delta+\epsilon_1) dG(\epsilon_2) + \int_{\epsilon_1+\Delta}^{\delta} (q_2+\epsilon_2-q_2) dG(\epsilon_2) \Big) dG(\epsilon_1) \Big] dF(\alpha) \\ + \int_{\underline{\alpha}}^{\overline{\alpha}} q_2 Q_2^B(\alpha) dF(\alpha).$$

The total learning cost is given by

$$TC^B = c\, m_L^B = \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha) \Big[\int_{-\delta}^{-\bar{\epsilon}-\Delta} c\, dG(\epsilon_1) + \int_{\bar{\epsilon}-\Delta}^{\delta} c\, dG(\epsilon_1) + \int_{-\bar{\epsilon}-\Delta}^{\bar{\epsilon}-\Delta} 2c\, dG(\epsilon_2) \Big] dF(\alpha).$$

Next, consider DA and suppose that students with $\alpha > \alpha^*$ learn ϵ_1 first. Then, $SW^D = MV^D - TC^D$. Note that

$$MV_1^D = \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha) \Big[\int_{\bar{\epsilon}(\alpha)-\Delta}^{\delta} (q_1+\epsilon_1) dG(\epsilon_1) + \int_{-\bar{\epsilon}(\alpha)-\Delta}^{\bar{\epsilon}(\alpha)-\Delta} \int_{-\delta}^{\epsilon_1+\Delta} (q_1+\epsilon_1) dG(\epsilon_2) dG(\epsilon_1) \Big] dF(\alpha) \\ + \int_{\underline{\alpha}}^{\alpha^*} q_1 Q_1^D(\alpha) dF(\alpha),$$

$$MV_2^D = \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha) \Big[\int_{-\delta}^{-\bar{\epsilon}(\alpha)-\Delta} q_2 dG(\epsilon_1) + \int_{-\bar{\epsilon}(\alpha)-\Delta}^{\bar{\epsilon}(\alpha)-\Delta} \int_{\epsilon_1+\Delta}^{\delta} (q_2+\epsilon_2) dG(\epsilon_2) dG(\epsilon_1) \Big] dF(\alpha) \\ + \int_{\underline{\alpha}}^{\overline{\alpha}} q_2 (Q_2^D(\alpha) - Q_1^D(\alpha)) dF(\alpha)$$

and so $MV^D = MV_1^D + MV_2^D$ is

$$MV^D = \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha) \Big[\int_{\bar{\epsilon}(\alpha)-\Delta}^{\delta} (\Delta+\epsilon_1) dG(\epsilon_1) \\ + \int_{-\bar{\epsilon}(\alpha)-\Delta}^{\bar{\epsilon}(\alpha)-\Delta} \Big(\int_{-\delta}^{\epsilon_1+\Delta} (\Delta+\epsilon_1) dG(\epsilon_2) + \int_{\epsilon_1+\Delta}^{\delta} \epsilon_2 dG(\epsilon_2) \Big) dG(\epsilon_1) \Big] dF(\alpha) \\ + \int_{\underline{\alpha}}^{\overline{\alpha}} q_2 Q_2^D(\alpha) dF(\alpha) + \int_{\underline{\alpha}}^{\alpha^*} \Delta\, Q_1^D(\alpha) dF(\alpha), \tag{A.9}$$

and TC^D is written as

$$TC^D = c\, m_L^D = \int_{\alpha^*}^{\overline{\alpha}} \Big[\int_{-\delta}^{-\bar{\epsilon}(\alpha)-\Delta} c\, dG(\epsilon_1) + \int_{\bar{\epsilon}(\alpha)-\Delta}^{\delta} c\, dG(\epsilon_1) + \int_{-\bar{\epsilon}(\alpha)-\Delta}^{\bar{\epsilon}(\alpha)-\Delta} 2c\, dG(\epsilon_2) \Big] dF(\alpha). \tag{A.10}$$

We now establishes a series of lemmas that prove Theorem 2.

Lemma A4. $SW^B > SW^D$ *for any* r.

Proof. Note that

$$
\begin{aligned}
SW^B =& MV^B - TC^B \\
=& \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\Bigg[\int_{\underline{\epsilon}-\Delta}^{\delta}(\Delta+\epsilon_1-c)dG(\epsilon_1)+\int_{-\delta}^{\overline{\epsilon}-\Delta}(-c)dG(\epsilon_1) \\
&+\int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\bigg(\int_{-\delta}^{\epsilon_1+\Delta}(\Delta+\epsilon_1-2c)dG(\epsilon_2)+\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)\bigg)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&+\int_{\underline{a}}^{\overline{a}} Q_2^B(\alpha)q_2 dF(\alpha).
\end{aligned}
\tag{A.11}
$$

and

$$
\begin{aligned}
SW^D &= MV^D - TC^D \\
&\leq MV^D - \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\Bigg[\int_{-\delta}^{-\overline{\epsilon}(\alpha)-\Delta} c\,dG(\epsilon_1)+\int_{\overline{\epsilon}-\Delta}^{\delta} c\,dG(\epsilon_1)+\int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta} 2c\,dG(\epsilon_2)\Bigg]dF(\alpha) \\
&= \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta}(\Delta+\epsilon_1-c)dG(\epsilon_1)+\int_{-\delta}^{\overline{\epsilon}(\alpha)-\Delta}(-c)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&\quad+\int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\bigg(\int_{-\delta}^{\epsilon_1+\Delta}(\Delta+\epsilon_1-2c)dG(\epsilon_2)+\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)\bigg)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&\quad+\int_{\underline{\alpha}}^{\overline{\alpha}} Q_2^D(\alpha)q_2\,dF(\alpha)+\int_{\underline{\alpha}}^{\alpha^*} Q_1^D(\alpha)\Delta\,dF(\alpha) \\
&\equiv \overline{SW}^D
\end{aligned}
\tag{A.12}
$$

Since $SW^B - SW^D \geq SW^B - \overline{SW}^D$, we show $SW^B > \overline{SW}^D$ in what follows. Note that

$$
\begin{aligned}
&SW^B - \overline{SW}^D \\
=& \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\Bigg[\int_{\underline{\epsilon}-\Delta}^{\delta}(\Delta+\epsilon_1-c)dG(\epsilon_1)+\int_{-\delta}^{\overline{\epsilon}-\Delta}(-c)dG(\epsilon_1) \\
&+\int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\bigg(\int_{-\delta}^{\epsilon_1+\Delta}(\Delta+\epsilon_1-2c)dG(\epsilon_2)+\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)\bigg)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&-\int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta}(\Delta+\epsilon_1-c)dG(\epsilon_1)+\int_{-\delta}^{\overline{\epsilon}(\alpha)-\Delta}(-c)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&+\int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\bigg(\int_{-\delta}^{\epsilon_1+\Delta}(\Delta+\epsilon_1-2c)dG(\epsilon_2)+\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)\bigg)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&-\int_{\underline{\alpha}}^{\alpha^*}\Delta\,Q_1^D(\alpha)dF(\alpha)
\end{aligned}
$$

$$
\begin{aligned}
&= \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\Bigg[\int_{\underline{\epsilon}-\Delta}^{\delta}(\epsilon_1 - c)dG(\epsilon_1) + \int_{-\delta}^{\overline{\epsilon}-\Delta}(-c)dG(\epsilon_1) \\
&\qquad + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\Big(\int_{-\delta}^{\epsilon_1+\Delta}(\epsilon_1 - 2c)dG(\epsilon_2) + \int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2 - 2c)dG(\epsilon_2)\Big)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&- \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta}(\epsilon_1 - c)dG(\epsilon_1) + \int_{-\delta}^{\overline{\epsilon}(\alpha)-\Delta}(-c)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&\qquad + \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\Big(\int_{-\delta}^{\epsilon_1+\Delta}(\epsilon_1 - 2c)dG(\epsilon_2) + \int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2 - 2c)dG(\epsilon_2)\Big)dG(\epsilon_1)\Bigg]dF(\alpha).
\end{aligned}
$$

The first equality follows from the fact that

$$\int_{\underline{\alpha}}^{\overline{\alpha}} Q_2^B(\alpha)dF(\alpha) = 2\kappa = \int_{\underline{\alpha}}^{\overline{\alpha}} Q_2^D(\alpha)dF(\alpha),$$

and to understand the second equality, observe that

$$
\begin{aligned}
k = \mathfrak{m}_1^D = \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta} 1dG(\epsilon_1) + \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\Big(\int_{-\delta}^{\epsilon_1+\Delta} 1dG(\epsilon_2)\Big)dG(\epsilon_2)\Bigg]dF(\alpha) \\
+ \int_{\underline{\alpha}}^{\alpha*} Q_1^D(\alpha)dF(\alpha),
\end{aligned}
\tag{A.13}
$$

so, we have

$$
\begin{aligned}
&\int_{\underline{\alpha}}^{\alpha^*} \Delta Q_1^D(\alpha)dF(\alpha) \\
&= \Delta\,\kappa - \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta} \Delta dG(\epsilon_1) + \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\Big(\int_{-\delta}^{\epsilon_1+\Delta} \Delta dG(\epsilon_2)\Big)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&= \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\Bigg[\int_{\overline{\epsilon}-\Delta}^{\delta} \Delta dG(\epsilon_1) + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\Big(\int_{-\delta}^{\epsilon_1+\Delta} \Delta dG(\epsilon_2)\Big)dG(\epsilon_1)\Bigg]dF(\alpha) \\
&\quad - \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta} \Delta dG(\epsilon_1) + \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\Big(\int_{-\delta}^{\epsilon_1+\Delta} \Delta dG(\epsilon_2)\Big)dG(\epsilon_1)\Bigg]dF(\alpha),
\end{aligned}
$$

where the last equality follows from the capacity constraint of college 1 in the benchmark, that is,

$$\mathfrak{m}_1^B = \int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)\Bigg[\int_{\overline{\epsilon}-\Delta}^{\delta} 1dG(\epsilon_1) + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\Big(\int_{-\delta}^{\epsilon_1+\Delta} 1dG(\epsilon_2)\Big)dG(\epsilon_1)\Bigg]dF(\alpha) = k. \tag{A.14}$$

Claim A2. $\int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)dF(\alpha) \geq \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)dF(\alpha)$.

Proof . Consider the terms in the square bracket of $\mathfrak{m}_1^B$ and $\mathfrak{m}_1^D$ in (A.14) and (A.13), respectively. Observe that for any fixed α,

$$\begin{aligned}
&\left[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta} 1dG(\epsilon_1) + \int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta} 1dG(\epsilon_2)\right)dG(\epsilon_2)\right] \\
&-\left[\int_{\overline{\epsilon}-\Delta}^{\delta} 1dG(\epsilon_1) + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta} 1dG(\epsilon_2)\right)dG(\epsilon_1)\right] \\
&= \int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta} 1dG(\epsilon_1) - \int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta} G(\epsilon_1+\Delta)dG(\epsilon_1) - \int_{-\overline{\epsilon}-\Delta}^{-\overline{\epsilon}(\alpha)-\Delta} G(\epsilon_1+\Delta)dG(\epsilon_1) \\
&= \int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta} (1-G(\epsilon_1+\Delta))dG(\epsilon_1) - \int_{-\overline{\epsilon}-\Delta}^{-\overline{\epsilon}(\alpha)-\Delta} G(\epsilon_1+\Delta)dG(\epsilon_1) \\
&= \int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta} G(-\epsilon_1-\Delta)dG(\epsilon_1) - \int_{-\overline{\epsilon}-\Delta}^{-\overline{\epsilon}(\alpha)-\Delta} G(\epsilon_1+\Delta)dG(\epsilon_1) = 0,
\end{aligned}$$

where the last equality holds since

$$\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta} G(-\epsilon_1-\Delta)dG(\epsilon_1) = \int_{-\overline{\epsilon}}^{-\overline{\epsilon}(\alpha)} G(t)dG(t-\Delta) = \int_{-\overline{\epsilon}-\Delta}^{-\overline{\epsilon}(\alpha)-\Delta} G(\eta+\Delta)dG(\eta),$$

form a sequence of change of variables $t = -\epsilon_1 - \Delta$ and $\eta = t - \Delta$. Thus, we have

$$\mathfrak{m}_1^D = \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)dF(\alpha)\left[\int_{\overline{\epsilon}-\Delta}^{\delta} 1dG(\epsilon_1)+\int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta} 1dG(\epsilon_2)\right)dG(\epsilon_1)\right]+\int_{\underline{\alpha}}^{\alpha*} Q_1^C(\alpha)dF(\alpha).$$

and from the fact that $\mathfrak{m}_1^B = k = \mathfrak{m}_1^D$, we further have

$$\begin{aligned}
&\left(\int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)dF(\alpha) - \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)dF(\alpha)\right)\left[\int_{\overline{\epsilon}-\Delta}^{\delta} 1dG(\epsilon_1) + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta} 1dG(\epsilon_2)\right)dG(\epsilon_1)\right] \\
&= \int_{\underline{\alpha}}^{\alpha^*} Q_1^D(\alpha)dF(\alpha) \geq 0,
\end{aligned}$$

which yields the desired result.□

Now, using Claim A2, we have

$$\begin{aligned}
&SW^B - \overline{SW} \\
&\geq \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\left[\int_{\underline{\epsilon}-\Delta}^{\delta}(\epsilon_1-c)dG(\epsilon_1) + \int_{-\delta}^{\overline{\epsilon}-\Delta}(-c)dG(\epsilon_1)\right. \\
&\qquad\left. + \int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta}(\epsilon_1-2c)dG(\epsilon_2) + \int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)\right)dG(\epsilon_1)\right]dF(\alpha) \\
&\quad - \int_{\alpha^*}^{\overline{\alpha}} Q_1^D(\alpha)\left[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\delta}(\epsilon_1-c)dG(\epsilon_1) + \int_{-\delta}^{\overline{\epsilon}(\alpha)-\Delta}(-c)dG(\epsilon_1)\right]dF(\alpha)
\end{aligned}$$

$$+\int_{-\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta}(\epsilon_1-2c)dG(\epsilon_2)+\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)\right)dG(\epsilon_1)\Bigg]dF(\alpha)$$

$$=\int_{\alpha^*}^{\overline{\alpha}}Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta}(\epsilon_1-2c)dG(\epsilon_2)+\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)-(\epsilon_1-c)\right)dG(\epsilon_1)$$

$$+\int_{-\overline{\epsilon}-\Delta}^{-\overline{\epsilon}(\alpha)-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta}(\epsilon_1-2c)dG(\epsilon_2)+\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-2c)dG(\epsilon_2)-(-c)\right)dG(\epsilon_1)\Bigg]dF(\alpha)$$

$$=\int_{\alpha^*}^{\overline{\alpha}}Q_1^D(\alpha)\Bigg[\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-(\epsilon_1+\Delta))dG(\epsilon_2)-c\right)dG(\epsilon_1)$$

$$+\int_{-\overline{\epsilon}-\Delta}^{-\overline{\epsilon}(\alpha)-\Delta}\left(\int_{-\delta}^{\epsilon_1+\Delta}((\epsilon_1+\Delta)-\epsilon_2)dG(\epsilon_2)-c\right)dG(\epsilon_1)\Bigg]dF(\alpha)>0.$$

To see the last inequality, observe that

$$\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{\epsilon_1+\Delta}^{\delta}(\epsilon_2-(\epsilon_1+\Delta))dG(\epsilon_2)-c\right)dG(\epsilon_1)$$

$$=\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{\epsilon_1+\Delta}^{\delta}\epsilon_2 dG(\epsilon_2)-(\epsilon_1+\Delta)(1-G(\epsilon_1+\Delta))-c\right)dG(\epsilon_1)$$

$$=\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\delta-(\epsilon_1+\Delta)G(\epsilon_1+\Delta)-\int_{\epsilon_1+\Delta}^{\delta}G(\epsilon_2)d\epsilon_2-(\epsilon_1+\Delta)(1-G(\epsilon_1+\Delta))-c\right)dG(\epsilon_1)$$

$$=\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\delta-(\epsilon_1+\Delta)-\int_{\epsilon_1+\Delta}^{\delta}G(\epsilon_2)d\epsilon_2-\int_{\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon\right)dG(\epsilon_1)$$

$$=\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\overline{\epsilon}-(\epsilon_1+\Delta)-\int_{\epsilon_1+\Delta}^{\overline{\epsilon}}G(\epsilon_2)d\epsilon_2\right)dG(\epsilon_1)=\int_{\overline{\epsilon}(\alpha)-\Delta}^{\overline{\epsilon}-\Delta}\left(\int_{\epsilon_1+\Delta}^{\overline{\epsilon}}(1-G(\epsilon_2))d\epsilon_2\right)dG(\epsilon_1)>0$$

where the second equality follows from the integration by parts, and the third equality follows from the definition of $\overline{\epsilon}$. Similarly, we also have

$$\int_{-\overline{\epsilon}-\Delta}^{\overline{\epsilon}(\alpha)-\Delta}\left(\int_{-\delta}^{\overline{\epsilon}(\alpha)-\Delta}((\epsilon_1+\Delta)-\epsilon_2)dG(\epsilon_2)-c\right)dG(\epsilon_1)>0.$$

Therefore, we have $SW^B > SW^D$ for any $r \in [0,1)$. ■

Lemma A5. *SW^B is invariant in r, and $SW^D = SW^B$ at $r = 1$.*

Proof. To show that SW^B is invariant in r, it suffices to show that $\int_{\underline{\alpha}}^{\overline{\alpha}} Q_i^B(\alpha)dF(\alpha)$ is invariant in r for all $i = 1, 2$. This is clear from (A.14), $\int_{\underline{\alpha}}^{\overline{\alpha}} Q_1^B(\alpha)dF(\alpha)$ is a constant. Using this and $\mathfrak{m}_2^B = k$, it also follows that $\int_{\underline{\alpha}}^{\overline{\alpha}} Q_2^B(\alpha)dF(\alpha)$ does not depend on r.

Next, consider the case that $r = 1$ so that $s = \alpha$ for each α. In the benchmark, there are $\hat{\alpha}_1^B > \hat{\alpha}_2^B$ such that $Q_1^B(\alpha) = \mathbb{1}_{\{\alpha\geq\hat{\alpha}_1^B\}}$ and $Q_2^B(\alpha) = \mathbb{1}_{\{\alpha\geq\hat{\alpha}_2^B\}}$. Except for this, students' learning decisions are the same as before. Similarly, in DA, there are $\hat{\alpha}_1^D > \hat{\alpha}_2^D$ such that $Q_1^D(\alpha) = \mathbb{1}_{\{\alpha\geq\hat{\alpha}_1^D\}}$ and $Q_2^D(\alpha) = \mathbb{1}_{\{\alpha\geq\hat{\alpha}_2^D\}}$, and students' learning decisions are the same as before. Thus,

$\overline{c}(\alpha) = Q_1^D(\alpha)\overline{c}$ is the same as $\overline{c}$ for $\alpha \geq \hat{a}_1^D$ and zero otherwise, and $Q_1^D(\alpha)\int_{\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon$ is these same as $\int_{\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon$ and zero otherwise. Therefore, $\hat{\alpha}_i^B = \hat{\alpha}_i^D$ for all $i = 1, 2$ and, consequently, $MV_i^B = MV_i^D$ and $TC^B = TC^D$. ∎

Lemma A6. *Suppose* $\Delta = 0$*. Then,* SW^D *increases with* r*.*

Proof. The proof consists of several steps: we first show that $\hat{s}_1 = \hat{s}_2$ in equilibrium and then show that SW^D increases with r.

Step 1. $\hat{s}_1 = \hat{s}_2$.

Proof . Suppose $\hat{s}_i > \hat{s}_j$. Then, students with $s \geq \hat{s}_i$ can attend whichever college they rank higher, while those with $s \in [\hat{s}_j, \hat{s}_i)$ will be assigned to college j. For the former group, the mass of students who prefer college 1 over college 2 (and 2 over 1) is given by (A.7) and (A.8), with $\Delta = 0$. That is,

$$m_{12} = \int_{\alpha^*}^{\overline{\alpha}} Q_i(\alpha)\left[1 - G(\overline{\epsilon}(\alpha)) + \int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} G(\epsilon_1)dG(\epsilon_1)\right]dF(\alpha),$$

$$m_{21} = \int_{\alpha^*}^{\overline{\alpha}} Q_i(\alpha)\left[G(-\overline{\epsilon}(\alpha)) + \int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} (1 - G(\epsilon_1))dG(\epsilon_1)\right]dF(\alpha).$$

For a given α, the symmetry of $G(\cdot)$ implies that $1 - G(\overline{\epsilon}(\alpha)) = G(-\overline{\epsilon}(\alpha))$ and

$$\int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} (1 - G(\epsilon_1))dG(\epsilon_1) = \int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} G(-\epsilon_1)dG(\epsilon_1) = \int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} G(\epsilon_1)dG(\epsilon_1).$$

Therefore, $m_{12} = m_{21}$, which leads to a contradiction: either college i does not fill its capacity, or college j exceeds its capacity. Hence, it must be that $\hat{s}_1 = \hat{s}_2$. □

Step 2. $\frac{dQ(\alpha)}{dr} = \frac{\alpha - \mathbb{E}[\alpha]}{2\eta(1-r)^2}$.

Proof . Denote by $\hat{s} := \hat{s}_1 = \hat{s}_2$, and $Q_1(\alpha) = Q_2(\alpha) =: Q(\alpha) = \text{Prob}(s \geq \hat{s}|\alpha)$. Since $\theta \in [-\eta, \eta]$ follows the uniform distribution, we have $Q(\alpha) = 1 - \frac{1}{2\eta}\left(\frac{\hat{s} - r\alpha}{1-r} + \eta\right)$. Note that $\hat{s}$ is determined by the colleges' joint capacity constraint:

$$\int_{\underline{\alpha}}^{\overline{\alpha}} Q(\alpha)dF(\alpha) = 2k \iff \frac{1}{2\eta}\int_{\underline{\alpha}}^{\overline{\alpha}}\left(\frac{\hat{s} - r\alpha}{1-r} + \eta\right)dF(\alpha) = \frac{1}{2\eta}\left(\frac{\hat{s}}{1-r} - \frac{r}{1-r}\mathbb{E}[\alpha] + \eta\right) = 1 - 2k,$$

so $\hat{s} = r\mathbb{E}[\alpha] + \eta(1-r)(1-4k)$. Substituting this into $Q(\alpha)$ above, we have

$$Q(\alpha) = 1 - \frac{\frac{r(\mathbb{E}[\alpha]-\alpha)}{1-r} + \eta(1-4k) + \eta}{2\eta} \Rightarrow \frac{dQ(\alpha)}{dr} = \frac{\alpha - \mathbb{E}[\alpha]}{2\eta(1-r)^2}.$$

□

Step 3. *SW^D increases in r.*

Proof . From (A.9) and (A.10), we have

$$MV^D = \int_{\alpha^*}^{\overline{\alpha}} Q(\alpha)\Bigg[\underbrace{\int_{\overline{\epsilon}(\alpha)}^{\delta} \epsilon_1 dG(\epsilon_1) + \int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} \left(\int_{-\delta}^{\epsilon_1} \epsilon_1 dG(\epsilon_2) + \int_{\epsilon_1}^{\delta} \epsilon_2 dG(\epsilon_2)\right) dG(\epsilon_1)}_{=:\mathcal{E}}\Bigg] dF(\alpha)$$

$$+ \underbrace{\int_{\underline{\alpha}}^{\overline{\alpha}} qQ(\alpha)dF(\alpha),}_{=2kq}$$

$$TC^D = \int_{\alpha^*}^{\overline{\alpha}} \left[\int_{-\delta}^{-\overline{\epsilon}(\alpha)} cdG(\epsilon_1) + \int_{\overline{\epsilon}(\alpha)}^{\delta} cdG(\epsilon_1) + \int_{-\overline{\epsilon}(\alpha)}^{\overline{\epsilon}(\alpha)} 2cdG(\epsilon_2)\right] dF(\alpha),$$

where $\overline{\epsilon}(\alpha)$ satisfies $Q(\alpha)\int_{\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon = c$, and α^* satisfies $\overline{c}(\alpha^*) = c$ with $\overline{c}(\alpha)$ being given by $\overline{c}(\alpha) := Q(\alpha)\int_0^{\delta}(1 - G(\epsilon))d\epsilon$. Note that at $\alpha = \alpha^*$, $\overline{\epsilon}(\alpha)$ satisfies

$$Q(\alpha^*)\int_{\overline{\epsilon}}^{\delta}(1 - G(\epsilon)) = c = Q(\alpha^*)\int_0^{\delta}(1 - G(\epsilon))d\epsilon,$$

where the second equality follows from the definition of α^*. Hence, $\overline{\epsilon}(\alpha^*) = 0$.

Now, observe that

$$\begin{aligned}
\frac{dMV^D}{dr} &= -Q(\alpha^*)\left[\int_{\overline{\epsilon}(\alpha^*)}^{\delta} \epsilon_1 dG(\epsilon_1) + \int_{-\overline{\epsilon}(\alpha^*)}^{\overline{\epsilon}(\alpha^*)} \left(\int_{-\delta}^{\epsilon_1} \epsilon_1 dG(\epsilon_2) + \int_{\epsilon_1}^{\delta} \epsilon_2 dG(\epsilon_2)\right) dG(\epsilon_1)\right] f(\alpha^*)\frac{d\alpha^*}{dr} \\
&\quad + \int_{\alpha^*}^{\overline{\alpha}} \left(\frac{dQ(\alpha)}{dr}\mathcal{E} + Q(\alpha)\frac{d\mathcal{E}}{dr}\right) dF(\alpha) \\
&= -Q(\alpha^*)\int_0^{\delta} \epsilon_1 dG(\epsilon_1) f(\alpha^*)\frac{d\alpha^*}{dr} + \int_{\alpha^*}^{\overline{\alpha}} \left(\frac{dQ(\alpha)}{dr}\mathcal{E} + Q(\alpha)\frac{d\mathcal{E}}{dr}\right) dF(\alpha)
\end{aligned}$$

where the last equality holds since $\overline{\epsilon}(\alpha^*) = 0$. Note also that $\frac{d\mathcal{E}}{dr}$ is given by

$$\begin{aligned}
\frac{d\mathcal{E}}{dr} &= -\overline{\epsilon}(\alpha)g(\overline{\epsilon}(\alpha))\frac{d\overline{\epsilon}(\alpha)}{dr} + \left(\int_{-\delta}^{\overline{\epsilon}(\alpha)} \overline{\epsilon}(\alpha)dG(\epsilon_2) + \int_{\overline{\epsilon}(\alpha)}^{\delta} \epsilon_2 dG(\epsilon_2)\right) g(\overline{\epsilon}(\alpha))\frac{d\overline{\epsilon}(\alpha)}{dr} \\
&\quad + \left(\int_{-\delta}^{-\overline{\epsilon}(\alpha)} (-\overline{\epsilon}(\alpha))dG(\epsilon_2) + \int_{-\overline{\epsilon}(\alpha)}^{\delta} \epsilon_2 dG(\epsilon_2)\right) g(-\overline{\epsilon}(\alpha))\frac{d\overline{\epsilon}(\alpha)}{dr} \\
&= g(\overline{\epsilon}(\alpha))\frac{d\overline{\epsilon}(\alpha)}{dr}\left(-\overline{\epsilon}(\alpha) + \overline{\epsilon}(\alpha)G(\overline{\epsilon}(\alpha)) + \int_{\overline{\epsilon}(\alpha)}^{\delta} \epsilon_2 dG(\epsilon_2)\right) \\
&\quad + g(-\overline{\epsilon}(\alpha))\frac{d\overline{\epsilon}(\alpha)}{dr}\left(-\overline{\epsilon}(\alpha)G(-\overline{\epsilon}(\alpha)) + \int_{-\overline{\epsilon}(\alpha)}^{\delta} \epsilon_2 dG(\epsilon_2)\right) \\
&= \left[g(\overline{\epsilon}(\alpha))\left(-\overline{\epsilon}(\alpha) + \delta - \int_{\overline{\epsilon}(\alpha)}^{\delta} G(\epsilon_2)d\epsilon_2\right) + g(-\overline{\epsilon}(\alpha))\left(\delta - \int_{-\overline{\epsilon}(\alpha)}^{\delta} G(\epsilon_2)d\epsilon_2\right)\right]\frac{d\overline{\epsilon}(\alpha)}{dr}
\end{aligned}$$

$$= \left[g(\overline{\epsilon}(\alpha))\left(\int_{\overline{\epsilon}(\alpha)}^{\delta}(1-G(\epsilon))d\epsilon\right) + g(-\overline{\epsilon}(\alpha))\left(-\overline{\epsilon}(\alpha) + \int_{-\overline{\epsilon}(\alpha)}^{\delta}(1-G(\epsilon))d\epsilon_2\right)\right]\frac{d\overline{\epsilon}(\alpha)}{dr}$$
$$= \left[g(\overline{\epsilon}(\alpha) + g(-\overline{\epsilon}(\alpha))\right]\int_{\overline{\epsilon}(\alpha)}^{\delta}(1-G(\epsilon))d\epsilon\frac{d\overline{\epsilon}(\alpha)}{dr},$$

where the last equality holds since $-\overline{\epsilon} + \int_{-\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon = \int_{\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon$ by Claim A1.

Next, observe also that

$$\frac{dTC}{dr} = -\Big\{c + c\big[G(\overline{\epsilon}(\alpha^*)) - G(-\overline{\epsilon}(\alpha^*))\big]\Big\}f(\alpha^*)\frac{d\alpha^*}{dr} + \int_{\alpha^*}^{\overline{\alpha}} c\big[g(\overline{\epsilon}(\alpha)) + cg(-\overline{\epsilon}(\alpha))\big]\frac{d\overline{\epsilon}(\alpha)}{d\alpha}dF(\alpha)$$
$$= -cf(\alpha^*)\frac{d\alpha^*}{dr} + \int_{\alpha^*}^{\overline{\alpha}} c\big[g(\overline{\epsilon}(\alpha)) + cg(-\overline{\epsilon}(\alpha))\big]\frac{d\overline{\epsilon}(\alpha)}{dr}dF(\alpha),$$

where the last equality holds since $\overline{\epsilon}(\alpha^*) = 0$ so $G(\overline{\epsilon}(\alpha^*)) = G(-\overline{\epsilon}(\alpha^*)) = G(0)$.

Therefore, after arranging terms, it follows that

$$\frac{dSW^D}{dr} = \frac{dMV^D}{dr} - \frac{dTC^D}{dr}$$
$$= \int_{\alpha^*}^{\overline{\alpha}} \frac{dQ(\alpha)}{dr}\mathcal{E}dF(\alpha) + \int_{\alpha^*}^{\overline{\alpha}}\left\{Q(\alpha)\frac{d\mathcal{E}}{dr} - c\big[g(\overline{\epsilon}(\alpha)) + cg(-\overline{\epsilon}(\alpha))\big]\frac{d\overline{\epsilon}(\alpha)}{dr}\right\}dF(\alpha)$$
$$+ f(\alpha^*)\frac{d\alpha^*}{dr}\left[-Q(\alpha^*)\int_0^{\delta}\epsilon dG(\epsilon) + c\right]$$
$$= \int_{\alpha^*}^{\overline{\alpha}} \frac{dQ(\alpha)}{dr}\mathcal{E}dF(\alpha),$$

where the last equality holds since

$$\int_{\alpha^*}^{\overline{\alpha}}\left\{Q(\alpha)\frac{d\mathcal{E}}{dr} - c\big[g(\overline{\epsilon}(\alpha)) + cg(-\overline{\epsilon}(\alpha))\big]\frac{d\overline{\epsilon}(\alpha)}{d\alpha}\right\}dF(\alpha)$$
$$= \int_{\alpha^*}^{\overline{\alpha}}\left[Q(\alpha)\int_{\overline{\epsilon}(\alpha)}^{\delta}(1-G(\epsilon))d\epsilon - c\right]g(\overline{\epsilon}(\alpha))\frac{d\overline{\epsilon}(\alpha)}{dr}dF(\alpha)$$
$$+ \int_{\alpha^*}^{\overline{\alpha}}\left[Q(\alpha)\left(-\overline{\epsilon}(\alpha) + \int_{-\overline{\epsilon}(\alpha)}^{\delta}(1-G(\epsilon))d\epsilon\right) - c\right]g(-\overline{\epsilon}(\alpha))\frac{d\overline{\epsilon}(\alpha)}{dr}dF(\alpha) = 0$$

by definition of $\overline{\epsilon}(\alpha)$ (recall that $-\overline{\epsilon} + \int_{-\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon = \int_{\overline{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon = c$), and

$$Q(\alpha^*)\int_0^{\delta}\epsilon dG(\epsilon) = Q(\alpha^*)\int_0^{\delta}(1-G(\epsilon))d\epsilon = c$$

by definition of α^*. Next, observe that $\mathcal{E}$ is increasing in α, since

$$\frac{d\mathcal{E}}{d\alpha} = \left[g(\overline{\epsilon}(\alpha) + g(-\overline{\epsilon}(\alpha))\right]\int_{\overline{\epsilon}(\alpha)}^{\delta}(1-G(\epsilon))d\epsilon\frac{d\overline{\epsilon}(\alpha)}{d\alpha}$$

and $\bar{\epsilon}(\alpha)$ is increasing in α. Hence, we have

$$\frac{dSW^D}{dr} = \int_{\alpha^*}^{\overline{\alpha}} \frac{dQ(\alpha)}{dr}\mathcal{E}dF(\alpha) \geq \frac{1}{2\eta(1-r)^2}\int_{\alpha^*}^{\overline{\alpha}}(\alpha - \mathbb{E}[\alpha])dF(\alpha)\int_{\alpha^*}^{\overline{\alpha}}\mathcal{E}dF(\alpha) \geq 0,$$

where the first inequality follows from the fact that the covariance of increasing functions of a random variable is positive, and the last inequality holds since

$$\begin{aligned}\int_{\alpha^*}^{\overline{\alpha}}(\alpha - \mathbb{E}[\alpha])dF(\alpha) &= \int_{\alpha^*}^{\overline{\alpha}}\alpha dF(\alpha) - \mathbb{E}[\alpha](1-F(\alpha^*)) = (1-F(\alpha^*))\left(\frac{\int_{\alpha^*}^{\overline{\alpha}}\alpha dF(\alpha)}{1-F(\alpha^*)} - \mathbb{E}[\alpha]\right)\\ &= (1-F(\alpha^*))\big(\mathbb{E}[\alpha|\alpha \geq \alpha^*] - \mathbb{E}[\alpha]\big) \geq 0.\end{aligned}$$

Thus, SW^D increases with r. □ ■

B Three Colleges with $\Delta = 0$ in Remark 1.

Consider the case of three colleges with $\Delta = 0$, that is, $q_1 = q_2 = q_3 \equiv q$. In this setting, we must have $\hat{s}_1 = \hat{s}_2 = \hat{s}_3 \equiv \hat{s}$ and we let $Q(\alpha) \coloneqq \text{Prob}(s \geq \hat{s}|\alpha)$.

To see students' learning decisions, consider a student who has already learned both ϵ_i and ϵ_j, with $\epsilon_i \geq \epsilon_j$. Note that the student's learning decision in this stage is the same as that under the baseline model since she only compares ϵ_i and ϵ_k. Specifically, if she does not learn ϵ_k, then she will rank college i highest if $\epsilon_i \geq 0$, and otherwise prefer either j or k. Her expected payoff in this case is $u(\epsilon_i;\alpha) = Q(\alpha)(q+\epsilon_i)$ if $\epsilon_i \geq 0$, and $u(\epsilon_i;\alpha) = Q(\alpha)q$ if $\epsilon_i < 0$. Now, suppose she also learns ϵ_k. Then, she will rank i above k if $\epsilon_i \geq \epsilon_k$, and k above i otherwise. Her expected payoff is then

$$\begin{aligned}u(\epsilon_k|\epsilon_i \geq \epsilon_j;\alpha) &= Q(\alpha)\big\{\text{Prob}(\epsilon_i \geq \epsilon_k)(q+\epsilon_i) + \text{Prob}(\epsilon_i < \epsilon_k)\mathbb{E}[q+\epsilon_k|\epsilon_i < \epsilon_k]\big\}\\ &= Q(\alpha)\left[q + \epsilon_i + \int_{\epsilon_i}^{\delta}(1-G(\epsilon_k))d\epsilon_k\right] \qquad \text{(B.1)}\end{aligned}$$

Thus, the gain from learning ϵ_k is

$$u(\epsilon_k|\epsilon_i \geq \epsilon_j;\alpha) - u(\epsilon_i;\alpha) = \begin{cases}\int_{\epsilon_i}^{\delta}(1-G(\epsilon_k))d\epsilon_l & \text{if } \epsilon_i > 0\\ \epsilon_i + \int_{\epsilon_i}^{\delta}(1-G(\epsilon_k))d\epsilon_k & \text{if } \epsilon_i \leq 0.\end{cases}$$

Using Claim A1 and the same logic as in the baseline model, we conclude that the student learns ϵ_k in addition to $\epsilon_i > \epsilon_j$ if and only if $|\epsilon_i| < \bar{\epsilon}(\alpha)$, where $\bar{\epsilon}(\alpha)$ satisfies

$$Q(\alpha)\int_{\bar{\epsilon}}^{\delta}(1-G(\epsilon))d\epsilon = c.$$

Next, consider a student who has learned ϵ_i and decides whether to learn ϵ_j alone or both ϵ_j and ϵ_k. We analyze the cases $\epsilon_i > 0$ and $\epsilon_i \leq 0$ separately.

- Suppose $\epsilon_i > 0$. If the student does not learn ϵ_j (and hence not ϵ_k), her expected payoff is $u(\epsilon_i > 0; \alpha) = Q(\alpha)(q + \epsilon_i)$. If she learns ϵ_j only, she ranks college i highest if $\epsilon_i \geq \epsilon_j$, and ranks j highest otherwise. Her expected payoff becomes

$$\begin{aligned} u(\epsilon_j|\epsilon_i > 0;\alpha) &= Q(\alpha)\left\{\text{Prob}(\epsilon_i \geq \epsilon_j)(q+\epsilon_i) + \text{Prob}(\epsilon_i < \epsilon_j)\mathbb{E}[q+\epsilon_j|\epsilon_i < \epsilon_j]\right\} \\ &= Q(\alpha)\left[q + \epsilon_i + \int_{\epsilon_i}^{\delta}(1-G(\epsilon_j))d\epsilon_j\right] \end{aligned}$$

If she also learns ϵ_k, she ranks the college with the highest ϵ. So, her expected payoff is

$$\begin{aligned} u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) &= Q(\alpha)\left\{\text{Prob}(\epsilon_i \geq \epsilon_j)\mathbb{E}[u(\epsilon_k|\epsilon_i \geq \epsilon_j;\alpha)] + \text{Prob}(\epsilon_i < \epsilon_j)\mathbb{E}[u(\epsilon_k|\epsilon_i < \epsilon_j;\alpha)]\right\} \\ &= Q(\alpha)\left\{q + \epsilon_i + \int_{\epsilon_i}^{\delta}(1-G(\epsilon_j)^2)d\epsilon_j\right\}, \end{aligned}$$

where the last equality follows from substituting (B.1) into $u(\epsilon_k|\epsilon_i \geq \epsilon_j;\alpha)$ and $u(\epsilon_k|\epsilon_i < \epsilon_j;\alpha)$ and rearranging terms. The gains from learning ϵ_j alone and from learning ϵ_k after ϵ_j are given by

$$\begin{aligned} u(\epsilon_j|\epsilon_i \geq 0;\alpha) - u(\epsilon_i \geq 0;\alpha) &= Q(\alpha)\int_{\epsilon_i}^{\delta}(1-G(\epsilon))d\epsilon, \\ u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) - u(\epsilon_j|\epsilon_i \geq 0;\alpha) &= Q(\alpha)\int_{\epsilon_i}^{\delta}(1-G(\epsilon_j))G(\epsilon_j)d\epsilon_j. \end{aligned}$$

Define $\hat{\epsilon}(\alpha)$ such that

$$Q(\alpha)\int_{\hat{\epsilon}}^{\delta}(1-G(\epsilon_j))G(\epsilon_j)d\epsilon_j = c.$$

Observe that $\hat{\epsilon}(\alpha) < \bar{\epsilon}(\alpha)$, since otherwise

$$\int_{\bar{\epsilon}}^{\delta}(1-G(\epsilon_i))d\epsilon_i = \int_{\hat{\epsilon}}^{\delta}(1-G(\epsilon_i))G(\epsilon_i))d\epsilon_i < \int_{\hat{\epsilon}}^{\delta}(1-G(\epsilon_i))d\epsilon_i \leq \int_{\bar{\epsilon}}^{\delta}(1-G(\epsilon_i)d\epsilon_i,$$

where the first equality follows the definitions of $\bar{\epsilon}(\alpha)$ and $\hat{\epsilon}(\alpha)$. This yields a contradiction. Hence, the value of learning ϵ_j given $\epsilon_i \geq 0$ is

$$\max\{u(\epsilon_j|\epsilon_i \geq 0;\alpha) - c, u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) - 2c\} = \begin{cases} u(\epsilon_j|\epsilon_i \geq 0,\alpha) - c & \text{if } \epsilon_i > \hat{\epsilon}(\alpha), \\ u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) - 2c & \text{if } \epsilon_i < \hat{\epsilon}(\alpha). \end{cases}$$

This exceeds $u(\epsilon_i \geq 0;\alpha)$ if and only if $\epsilon_i < \overline{\epsilon}(\alpha)$, since $\hat{\epsilon}(\alpha) < \overline{\epsilon}(\alpha)$.

- Suppose $\epsilon_i \leq 0$. If the student does not learn ϵ_j, she ranks either college j or k above i, and her expected payoff is $u(\epsilon_i \leq 0;\alpha) = Q(\alpha)q$. If she learns ϵ_j but not ϵ_k, she ranks college k highest if $\epsilon_j < 0$ and j highest if $\epsilon_j > 0$. Her expected payoff is

$$\begin{aligned} u(\epsilon_j|\epsilon_i \leq 0;\alpha) &= Q(\alpha)\big\{\text{Prob}(\epsilon_j \leq 0)q + \text{Prob}(\epsilon_j > 0 \geq \epsilon_i)\mathbb{E}[q + \epsilon_j|\epsilon_j > 0]\big\} \\ &= Q(\alpha)\left[q + \int_0^\delta (1 - G(\epsilon_j))d\epsilon_j\right] \end{aligned}$$

  If she also learns ϵ_k, she compares all three ϵ's, and her expected payoff is

$$u(\epsilon_k|\epsilon_i,\epsilon_j) = Q(\alpha)\left[q + \epsilon_i + \int_{\epsilon_i}^\delta (1 - G(\epsilon_j)^2))d\epsilon_j\right].$$

  The expected gains from learn ϵ_j alone and from learning ϵ_k after ϵ_j are respectively

$$\begin{aligned} u(\epsilon_j|\epsilon_i \leq 0;\alpha) - u(\epsilon_i \leq 0;\alpha) &= Q(\alpha)\int_0^\delta (1 - G(\epsilon_j))d\epsilon_j =: \overline{c}(\alpha), \\ u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) - u(\epsilon_j|\epsilon_i \leq 0;\alpha) &= Q(\alpha)\left[\epsilon_i + \int_{\epsilon_i}^\delta (1 - G(\epsilon_j))G(\epsilon_j)d\epsilon_j - \int_0^\delta (1 - G(\epsilon_j))d\epsilon_j\right]. \end{aligned}$$

  Note that the latter is increasing in ϵ_i,

$$\frac{d[u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) - u(\epsilon_j|\epsilon_i < 0;\alpha)]}{d\epsilon_i} = Q(\alpha)\big[1 - G(\epsilon_i) + G(\epsilon_i)^2\big] > 0,$$

  and is negative at $\epsilon_i = 0$: $u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) - u(\epsilon_j|\epsilon_i = 0;\alpha) = -Q(\alpha)\int_0^\delta (1 - G(\epsilon_j))^2 d\epsilon_j < 0$. Therefore, the value of learning ϵ_j given $\epsilon_i \leq 0$ is

$$\max\{u(\epsilon_j|\epsilon_i \leq 0,\alpha) - c, u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha) - 2c\} = u(\epsilon_j;\epsilon_i \leq 0,\alpha) - c,$$

  so the student will learn ϵ_j if and only if $c < \overline{c}(\alpha)$.

Lastly, we analyze students' learning decisions at the beginning—that is, whether to learn ϵ_i and subsequently ϵ_j and ϵ_k. If the student does not at all, her expected payoff is

$V_0(\alpha) := Q(\alpha)q$. If she learns ϵ_i but not ϵ_j and ϵ_k, then her expected payoff is

$$U(\epsilon_i;\alpha) = Q(\alpha)\{\text{Prob}(\epsilon_i > 0)\mathbb{E}[q+\epsilon_i|\epsilon_i \geq 0] + \text{Prob}(\epsilon_i \leq 0)q\} = Q(\alpha)\left[q + \int_0^\delta (1-G(\epsilon_i))d\epsilon_i\right].$$

If she further learns ϵ_j but not ϵ_k, her expected payoff is

$$\begin{aligned} U(\epsilon_i,\epsilon_j;\alpha) &= Q(\alpha)\{\text{Prob}(\epsilon_i > 0)\mathbb{E}[u(\epsilon_j|\epsilon_i > 0;\alpha)] + \text{Prob}(\epsilon_i \leq 0)\mathbb{E}[u(\epsilon_j|\epsilon_i \leq 0;\alpha)]\} \\ &= Q(\alpha)\left[q + \int_0^\delta (1-G(\epsilon_i)^2)d\epsilon_i\right]. \end{aligned}$$

If the student learns all three ϵ's, her expected payoff is

$$U(\epsilon_i,\epsilon_j,\epsilon_k;\alpha) = \mathbb{E}[u(\epsilon_k|\epsilon_i,\epsilon_j;\alpha)] = Q(\alpha)\left[q + \int_{-\delta}^\delta (1-G(\epsilon_i)^2)G(\epsilon_i)d\epsilon_i\right].$$

Therefore, the value of learning is given by

$$V(\alpha) := \max\{U(\epsilon_i;\alpha) - c, U(\epsilon_i,\epsilon_j;\alpha) - 2c, U(\epsilon_i,\epsilon_j,\epsilon_k;\alpha) - 3c\},$$

and the student will choose to learn ϵ_i if and only if $V(\alpha) > V_0(\alpha)$.

We define the following terms to capture the incremental gains from learning:

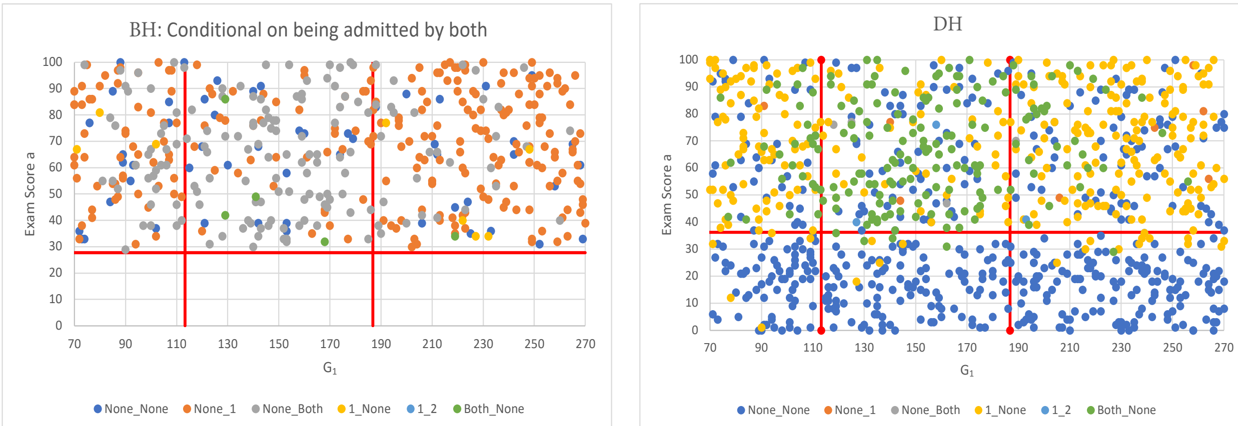
$$\begin{aligned} U(\epsilon_i;\alpha) - V_0(\alpha) &= Q(\alpha)\int_0^\delta (1-G(\epsilon))d\epsilon = \overline{c}(\alpha), \\ U(\epsilon_i,\epsilon_j;\alpha) - U(\epsilon_i;\alpha) &= Q(\alpha)\int_0^\delta (1-G(\epsilon))G(\epsilon)d\epsilon =: \hat{c}(\alpha), \\ U(\epsilon_i,\epsilon_j,\epsilon_k) - U(\epsilon_i,\epsilon_j;\alpha) &= Q(\alpha)\int_0^\delta (1-G(\epsilon))(2G(\epsilon)-1)d\epsilon =: \tilde{c}(\alpha). \end{aligned}$$

To compute $\tilde{c}(\alpha)$, observe that

$$\begin{aligned} &U(\epsilon_i,\epsilon_j,\epsilon_k) - U(\epsilon_i,\epsilon_j;\alpha) = Q(\alpha)\left[\int_{-\delta}^\delta (1-G(\epsilon)^2)G(\epsilon)d\epsilon - \int_0^\delta (1-G(\epsilon)^2)d\epsilon\right] \\ &= Q(\alpha)\left[\int_{-\delta}^0 (1-G(\epsilon)^2)G(\epsilon)d\epsilon - \int_0^\delta (1-G(\epsilon))(1-G(\epsilon)^2)d\epsilon\right] \\ &= Q(\alpha)\left[\int_0^\delta (1-(1-G(t))^2)(1-G(t))dt - \int_0^\delta (1-G(\epsilon))(1-G(\epsilon)^2)d\epsilon\right] \\ &= Q(\alpha)\left[\int_0^\delta (1-G(\epsilon))(2G(\epsilon)-1)d\epsilon\right] > 0, \end{aligned}$$

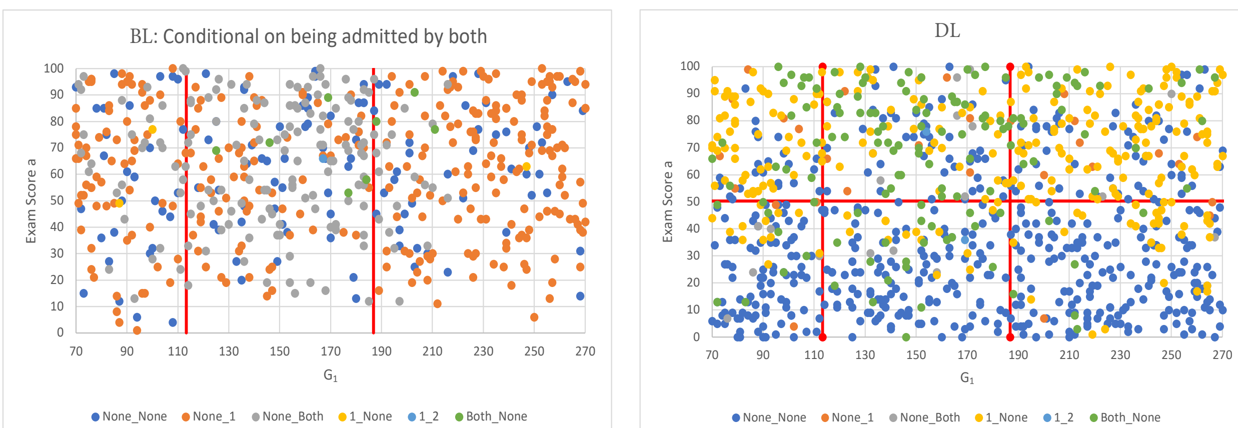
where the last inequality holds since $G(\epsilon) > \frac{1}{2}$ for any $\epsilon > 0$ by the symmetry of G. It is easy to see that $\tilde{c}(\alpha) < \hat{c}(\alpha) < \overline{c}(\alpha)$. Thus, the student will learn ϵ_i if and only if $c < \overline{c}(\alpha)$.

C Additional Figures and Tables



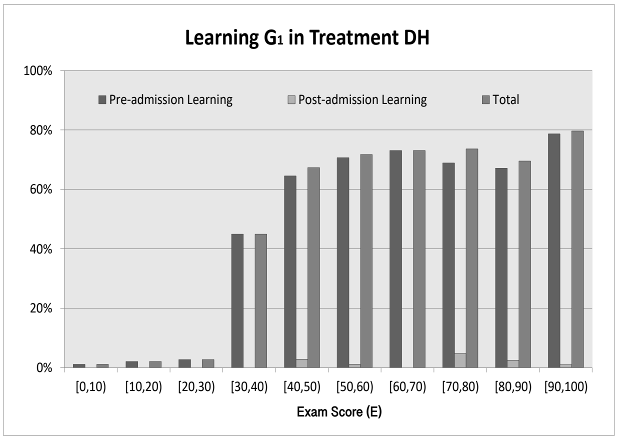
■ The label X_Y with $X, Y \in \{None, 1, 2, Both\}$ indicates that an individual learned the gain(s) from college(s) X in the pre-application stage and learned the gain(s) from college(s) Y in the post-admission stage.

Figure C1: High Transparency Treatments – Outcome Comparison



■ The label X_Y with $X, Y \in \{None, 1, 2, Both\}$ indicates that an individual learned the gain(s) from college(s) X in the pre-application stage and learned the gain(s) from college(s) Y in the post-admission stage.

Figure C2: Low Transparency Treatments – Outcome Comparison



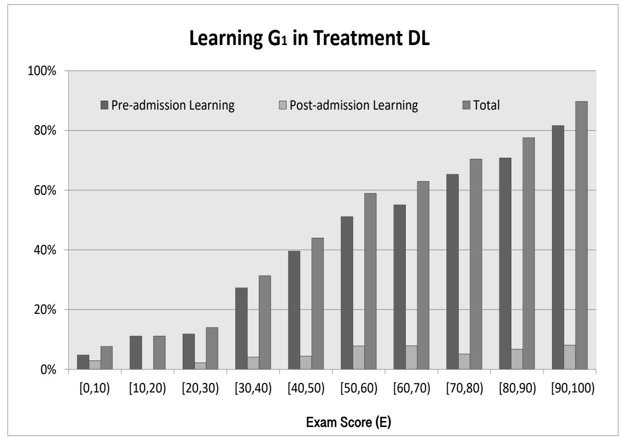
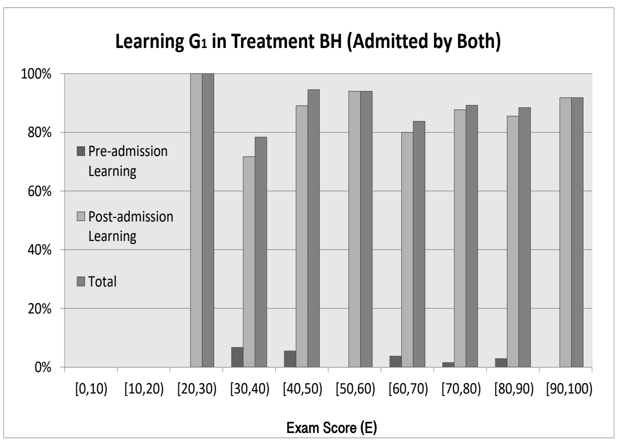


Figure C3: Learning G_1 in Treatments DH and DL - Histogram



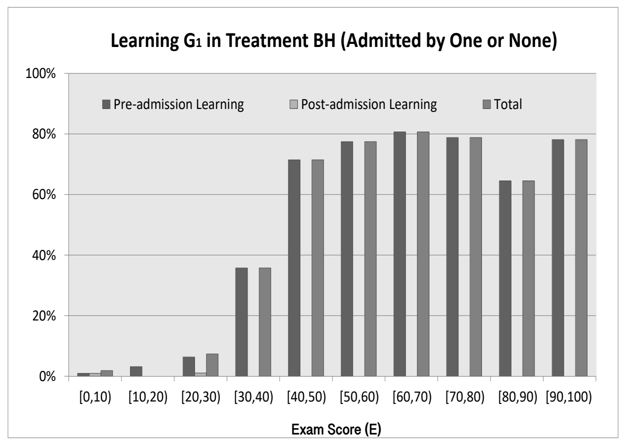
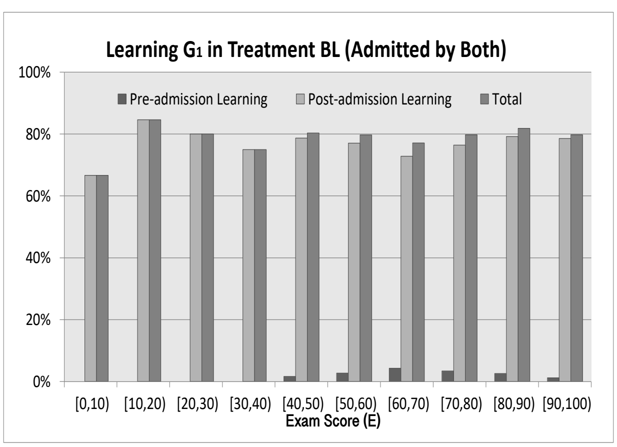


Figure C4: Learning G_1 in Treatment BH - Histogram



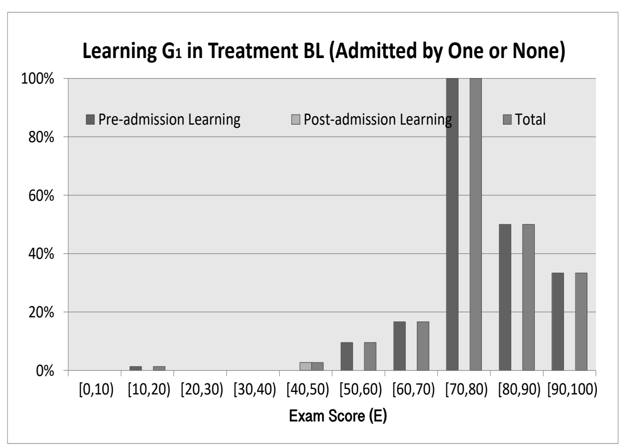


Figure C5: Learning G_1 in Treatment BL - Histogram

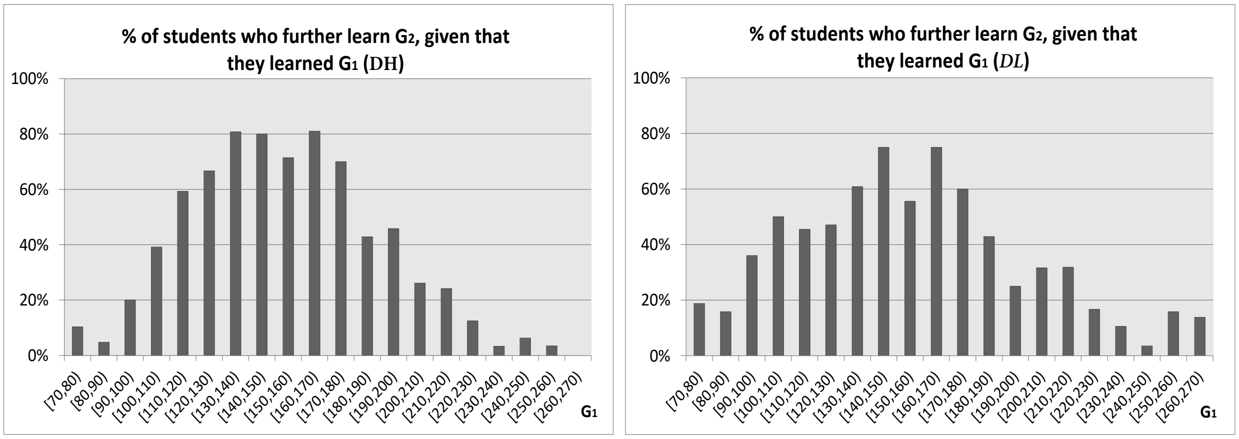


Figure C6: Learning G_2 in Treatments DH and DL - Histogram

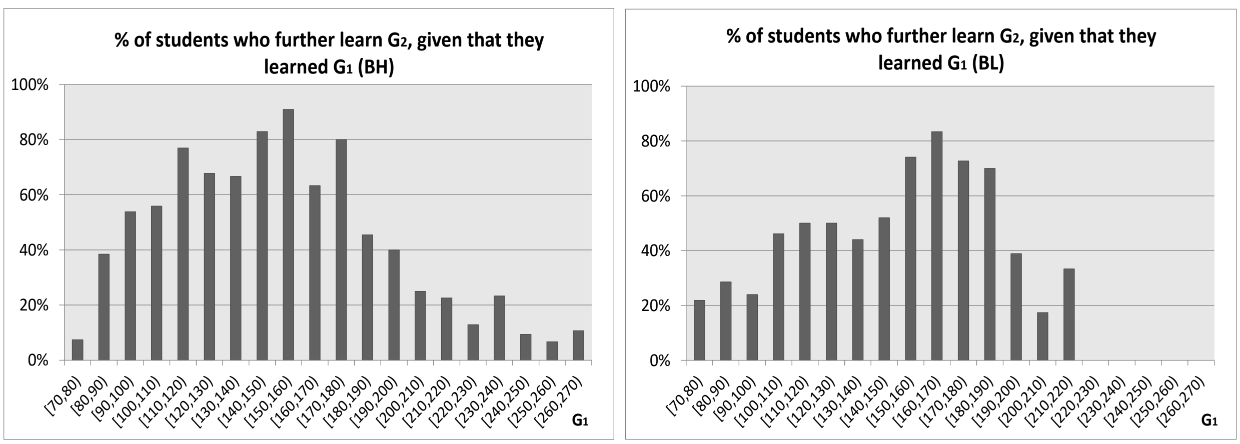


Figure C7: Learning G_2 in Treatments BH and BL - Histogram

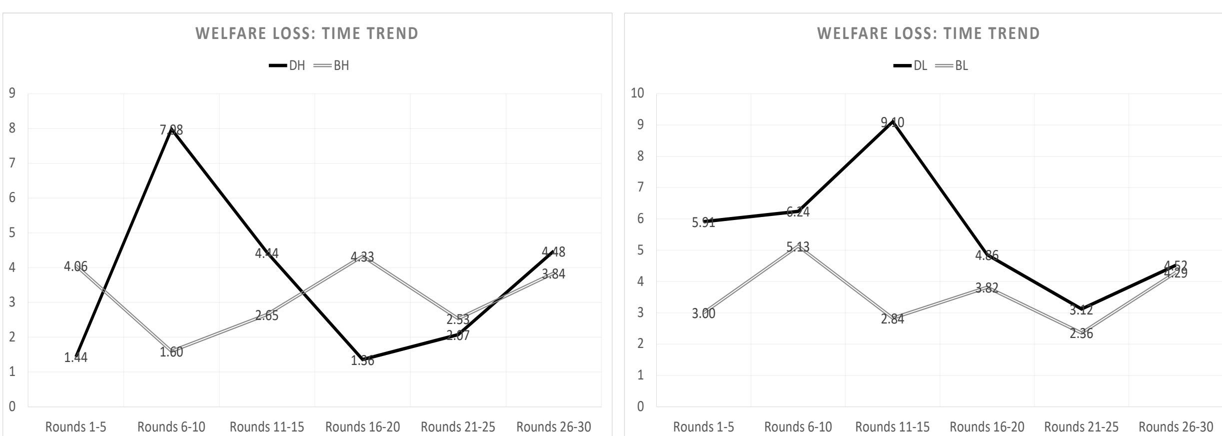


Figure C8: Welfare Loss - Time Trend

D Experimental Instructions

D.1 Treatment DH

Welcome to this experiment. Please read these instructions carefully. In the following one and a half hours or so, you will participate in 30 rounds of decision making. The payment you will receive from this experiment will depend on the decisions you make. The amount you earn will be paid **electronically via the HKUST Autopay System to the bank account you provide to the Student Information System (SIS)**. The auto-payment will be arranged by the Finance Office of HKUST, which takes about two weeks or more.

In this experiment, you are trying to enter a college. There are two colleges - College H and College K. The admission decision is based on your exam score and interview score, which will be further explained below.

Exam Score & Interview Score

At the beginning of each round, two scores will be generated for you according to the following procedure.

1. Exam Score (E): Your exam score is randomly drawn from $\{0, 1, 2, ..., 99, 100\}$.

   Each integer between 0 and 100 is equally likely to be drawn for your exam score. Then the exam score will be **announced to you**.

2. Interview Score (I): Your interview score is randomly drawn from $\{0, 1, 2, ..., 99, 100\}$.

   Each integer between 0 and 100 is equally likely to be drawn for your interview score. Your interview score will **not be revealed to you.**

   Note that the exam score and the interview score are independent with each other. That is, having higher or lower exam score E does not tell you anything about your interview score I.

3. Total Score (T): Your total score is calculated as follows.

$$\text{Total Score } (T) = 90\% \times E + 10\% \times I$$

Admission Procedure in Each College

After your exam score (E) is revealed to you, you (without knowing the total score) first need to decide if you want to send your application to College H, College K, or both colleges. There is no application fee at all.

Your application with your total score (T) is automatically sent to all college(s) you applied. Among the college(s) you applied, you will be admitted by a college if your **total score** (T) is higher than the following **admission cutoff**:

	College H	College K
Admission Cutoff (Total Score)	35	23

You will then receive admission(s) from none, one, or both of Colleges H and K. If you are admitted by only one college, you need to decide whether to pursue it or not. If you are admitted by both colleges, you need to decide whether to pursue none of them, College H, or College K.

Your Gain From College

Your gain from a college depends on how well the college suits you. More precisely,

- Your gain G_H (in tokens) from College H is randomly chosen between

  $$\{\mathbf{70}, \mathbf{71}, \mathbf{72}, ..., \mathbf{269}, \mathbf{270}\}.$$

  Each integer between 70 and 270 is equally likely to be drawn for your G_H. The gain G_H becomes part of your earning if College H admits you and you decide to pursue it.

- Your gain G_K (in tokens) from College K is randomly chosen between

  $$\{\mathbf{50}, \mathbf{51}, \mathbf{52}, ..., \mathbf{249}, \mathbf{250}\}.$$

  Each integer between 50 and 250 is equally likely to be drawn for your G_K. The gain G_K becomes part of your earning if College K admits you and you decide to pursue it.

Note that the gain G is college specific. That is, knowing G_H does not reveal anything about G_K, and vice versa.

Your Learning Decisions

G_H and G_K are **unknown** to you at the beginning of each round, but you will have opportunities to learn them. Learning incurs some costs to you.

Once each round begins, your decision screen always contains a panel that allows you to learn what the exact gain from College H (i.e., the value of G_H) is. The panel is randomly located either in the right half or in the left half of the screen. If you decide to learn it, you need to pay 10 tokens at the end of the round. Then you further decide whether to learn what the exact gain from College K (i.e., the value of G_K) is. If you decide to learn it, you need to pay additional 10 tokens at the end of the round.

Note that the options for you to learn G_H and G_K are **always** available in your decision screen and thus the following decisions are completely up to you:

1. **whether** to learn none/one/both of G_H and G_K and
2. **when** to learn them. You can learn none/one/both of them **before or after** the admission process begins or admission result is announced to you.

The learning cost you pay is constant at 10 tokens per college and does not depend on when you learn G_H and/or G_K.

Your Earnings

Your earning in each round will be

$$= \begin{cases} \text{Your Gain from Gollege} - \text{Cost of Learning You Paid}, & \text{if you pursue a college,} \\ \text{Default Gain (50 tokens)} - \text{Cost of Learning You Paid}, & \text{otherwise.} \end{cases}$$

For example,

1. Suppose that you paid 10 tokens and learned that $G_H = 150$, but decided to not learn G_K. You were admitted by College H and decided to pursue it. Your earning is 150 (Gain) - 10 (Cost of Learning) = 140.
2. Suppose that you paid 10 tokens and learned that $G_H = 150$. Then you further paid 10 tokens and learned that $G_K = 170$. It turned out that you were admitted by College K and decided to pursue it. Your earning is 170 (Gain) - 20 (Cost of Learning) = 150.
3. Suppose that you paid 10 tokens and learned that $G_H = 150$, but decided to not learn G_K. It turned out that you were admitted by College K and decided to pursue it. The realized gain was $G_K = 170$. Your earning is 170 (Gain) - 10 (Cost of Learning) = 160.
4. Suppose that you paid 10 tokens and learned that $G_H = 150$. Then you further paid 10 tokens and learned that $G_K = 170$. It turned out that you were not admitted by any college. Your earning is 50 (Default Gain) - 20 (Cost of Learning) = 30.
5. Suppose that you decided to not learn G_H nor G_K. It turned out that you were admitted by College K and decided to pursue it. The realized gain was $G_K = 180$. Your earning is 180 (Gain) - 0 (Cost of Learning) = 180.

Information Feedback

At the end of each round, the computer will provide you with some feedback, including 1) your exam score, 2) your interview score, 3) your total score, 4) which college(s) you are admitted, 5) which college you pursue, 6) your learning decisions, 7) your G_H and G_K (regardless of whether you paid to learn none, one, or both of them), and 8) your earning.

Your Payment

The computer randomly selects **1 round** out of the 30 rounds to calculate your cash payment. So it is in your best interest to take each round equally seriously. Your total payment in HKD will be the number of tokens you earned in the selected round (1 token = 1 HKD) plus a HKD 40 show-up fee.

A Practice Round

To ensure your understanding of the instructions, you will participate in a practice round. The practice round is part of the instructions and is not relevant to your cash payment. Its objective is to get you familiar with the computer interface and the flow of the decisions in each round. Once the practice round is over, the computer will tell you "The official rounds begin now!"

Completion of the Experiment

After the 30th round, the experiment will be over. You will be instructed to fill in the receipt for your payment. The amount you earn will be paid electronically via the HKUST Autopay System to the bank account you provide to the Student Information System (SIS). The auto-payment will be arranged by the Finance Office of HKUST.

[Round 0]

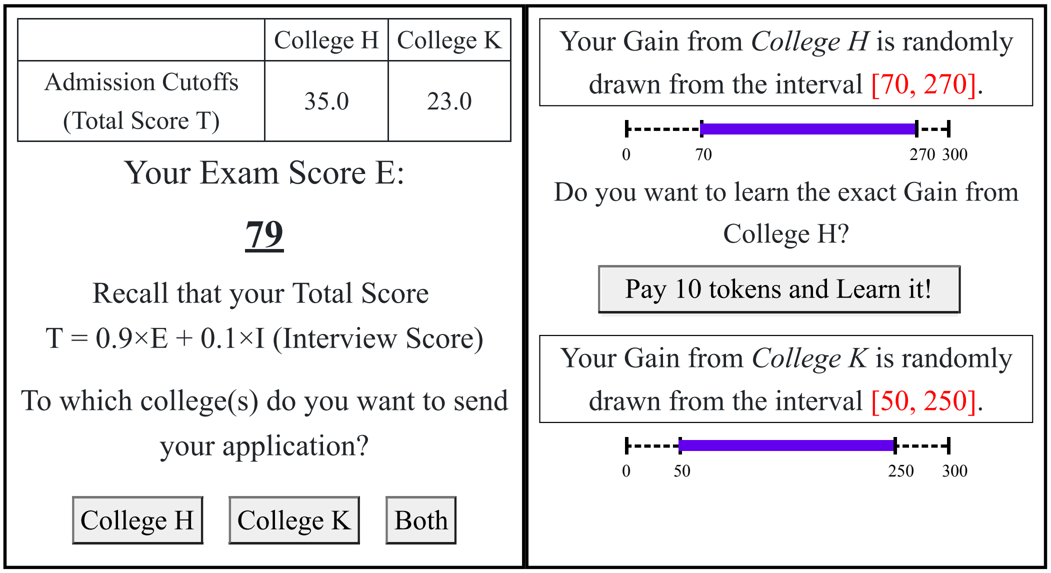


Figure D1: Screen Shot - Learning Panel on the Right

[Round 0]

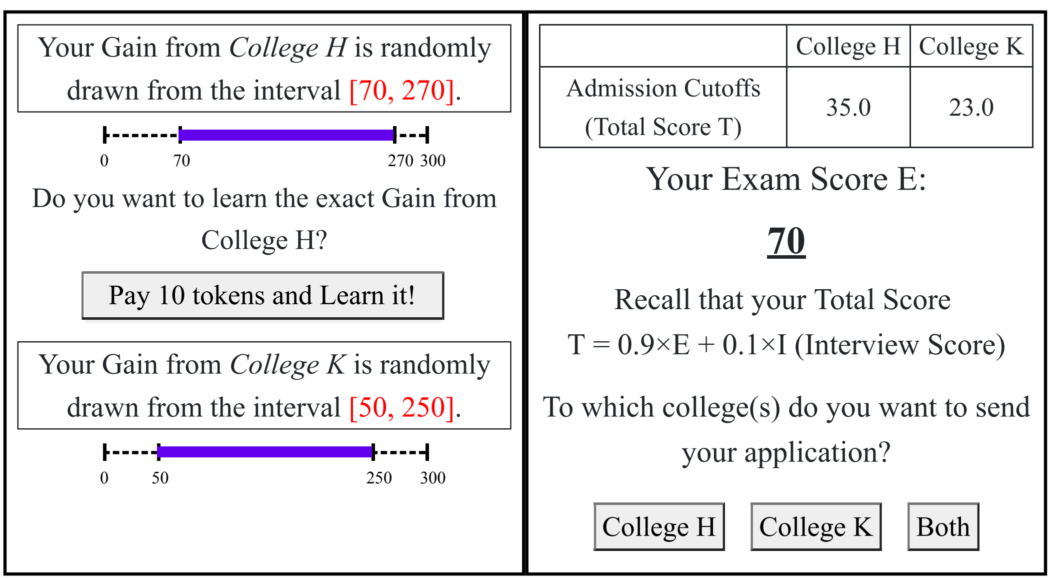


Figure D2: Screen Shot - Learning Panel on the Left

D.2 Treatment CH

Welcome to this experiment. Please read these instructions carefully. In the following one and a half hours or so, you will participate in 30 rounds of decision making. The payment you will receive from this experiment will depend on the decisions you make. The amount you earn will be paid **electronically via the HKUST Autopay System to the bank account you provide to the Student Information System (SIS)**. The auto-payment will be arranged by the Finance Office of HKUST, which takes about three weeks.

In this experiment, you are trying to enter a college. There are two colleges - College H and College K. They decide whether to admit you or not according to the following **centralized admission procedure**. First, you need to indicate your top choice between the two colleges to a central admission office. Second, the admission office makes admission decisions based on 1) the submitted rankings, and 2) your exam scores and interview scores, which will be further explained below.

Exam Score & Interview Score

At the beginning of each round, two scores will be generated for you according to the following procedure.

1. Exam Score (E): Your exam score is randomly drawn from $\{0, 1, 2, ..., 99, 100\}$.

   Each integer between 0 and 100 is equally likely to be drawn for your exam score. Then the exam score will be **announced to you**.

2. Interview Score (I): Your interview score is randomly drawn from $\{0, 1, 2, ..., 99, 100\}$.

   Each integer between 0 and 100 is equally likely to be drawn for your interview score. Your interview score will **not be revealed to you.**

   Note that the exam score and the interview score are independent with each other. That is, having higher or lower exam score E does not tell you anything about your interview score I.

3. Total Score (T): Your total score is calculated as follows.

$$\text{Total Score } (T) = 90\% \times E + 10\% \times I$$

Admission Procedure via Central Admission Office

After your exam score (E) is revealed to you, you (without knowing the total score) are asked to indicate your top choice between College H and College K as follows:

Please indicate your top choice:

College H *College K*

After you indicate your top choice, the admission procedure begins as follows:

1. The admission office sends your application to the college of your top choice.
2. The college accepts your application if your **total score** (T) is above the following **admission cutoff**, and reject otherwise:

	College H	College K
Admission Cutoff (Total Score)	36.3	23

3. If your application is accepted by the college of your top choice, the admission process is finalized.
4. Otherwise, the admission office sends your application to the college of your second choice.
5. The college decides whether to accept your application based on your total score T and the admission cutoff.
6. If your application is accepted by the college of your second choice, the admission process is finalized.
7. Otherwise, you are not admitted by any college and the process is finalized.

Note that the only thing you need to do is to indicate your top choice between College H and College K. All the steps described above take place in the admission system automatically, without any further inputs from you.

After the admission process is over, you will be informed whether you are admitted by College H, College K, or none of them. In case that you are admitted by a college, you need to decide whether to pursue the college or not.

Your Gain From College

Your gain from a college depends on how well the college suits you. More precisely,

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[Round 0]

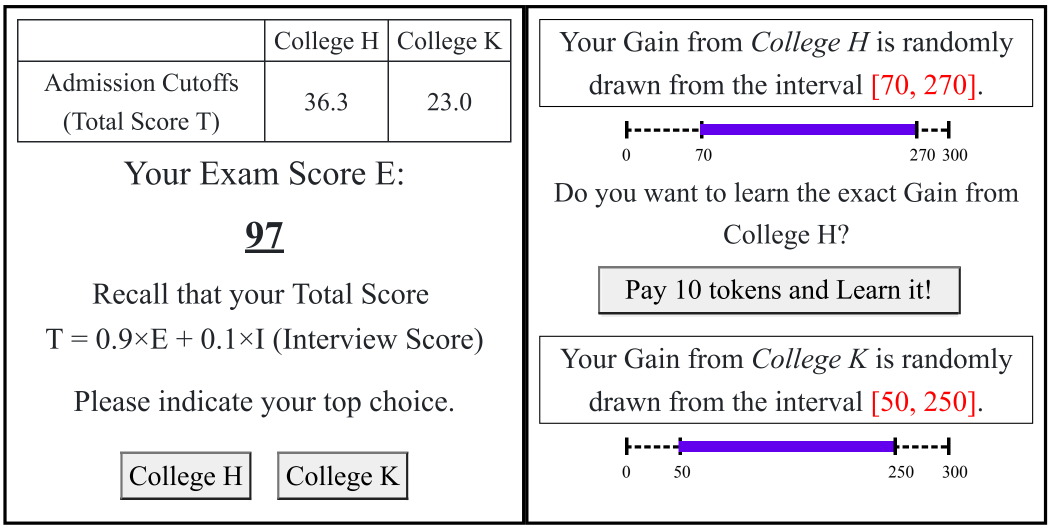

Figure D3: Screen Shot - Learning Panel on the Right

[Round 0]

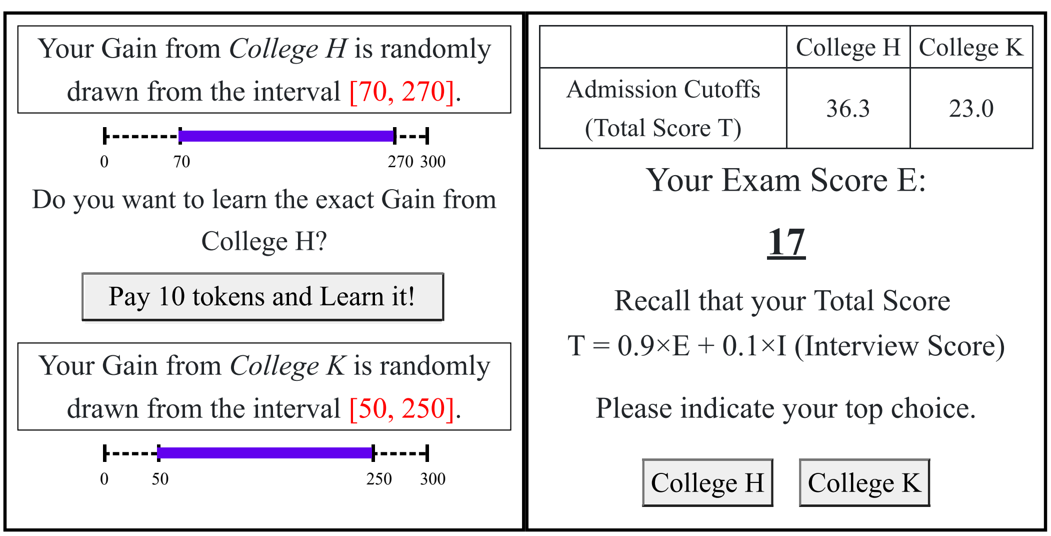

Figure D4: Screen Shot - Learning Panel on the Left