Information and Self-selection in School Choice: an Experiment*

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Abstract

We report on a multi-round experiment examining school choice under uncertainty. Admission to a school depends on a student's score relative to the school's cutoff. Participants submitted a rank-ordered list of schools only knowing the probability distribution of their score. At each round, participants could be either advantaged or disadvantaged, corresponding to a high and low probability to have a high score, respectively. Three types of school cutoffs were considered (capturing varying degree of competitiveness). In a control treatment, subjects were only given only the probability distribution of their score. In a second treatment, subjects were also given for each the probability to have a score higher than the school's cutoff. In a third and fourth treatment, subjects were given for each school the composition of advantaged and disadvantaged students (simulated for the third treatment, using subjects' choices of the third treatment for the fourth treatment).

For all treatments, subjects' selects lower ranked schools when they are disadvantaged and when schools' cutoffs are less stringent. Treatment effects are stronger for advantaged students. Compared to control, advantaged students are more likely to selected low-payoff (resp. high-payoff) schools when receiving information about their chances (resp. schools' compositions). In terms of outcomes, information about chances lowers segregation, but information about composition had no significant effect on segregation. Data on decision time, a proxy for task difficulty, showed significant differences in decision time between advantaged and disadvantaged (disadvantaged take more time), but little significant difference across treatments, suggesting that the availability and type of information did not affect how much time participants took to make their choices.

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Keywords: School choice, uncertainty, information, segregation

1 Introduction

Why students self-select into lower-quality schools and how such behavior might be mitigated are two recurrent questions in the education literature. The concern is that self-selection carries significant costs: it reduces the accumulation of human capital when students fail to attend the schools that would best serve them, and it exacerbates inequality when disadvantaged students are disproportionately affected—see Hoxby and Avery (2013).

While a lack of information is frequently cited as a key driver of these misaligned choices, the evidence on the effectiveness of information interventions is mixed. Some studies show that providing students and families with additional information can improve decision-making, while others find only modest or even counterproductive effects (e.g., Ainsworth et al. (2023) and Hyman (2020)).[1]

The objective of this paper is to investigate in depth the role of information in self-selection. We contend that the issue is not only whether students have access to information, but also what type of information they receive. Moreover, the effect of information may depend on factors such as students' academic potential and the competitiveness of schools. In many real-world settings, students receive two kinds of information: (i) ex-ante information about their chances of admission (e.g., average test scores of admitted students), and (ii) ex-post information about school composition (e.g., the socioeconomic or academic profiles of enrolled students).[2]

To identify the mechanisms at play, we rely on a highly stylized lab experiment, transforming the school choice problem into a decision-theoretic one: admission to each school depends only on a student's score and a known cutoff, with no capacity constraints or strategic interaction. Our study isolates the effect of informational

[1] Hoxby and Avery (2013), for instance, find that policies such as campus visits or mentoring programs are unlikely to succeed for certain categories of students.

[2] Some policies are also providing individuals with information relative the the *value* of the schools (i.e., academic attaignment, placement, etc.). In this paper we abstract from that type of information.

dimensions, abstracting from other sources of school value such as placement outcomes. This design removes the confounding effects of anticipated competition with other students (see Chen and Sönmez (2006); Calsamiglia et al. (2010)), thereby shifting the focus to how information alone influences school selection.

Our conceptual framework builds on insights from behavioral decision theory, which has documented how different framings of equivalent information can lead to different choices. Classic results show that people react differently to gains vs. losses or success vs. failure depending on how information is presented (Tversky and Kahneman (1981)). Framing effects are particularly pronounced in environments involving risk and uncertainty, such as those involving probability judgments (Tversky and Kahneman (1974); Bruhin et al. (2010)). In line with this literature, we examine how different framings of the same probabilistic environment—ex-ante versus ex-post—shape school choice.

The experimental protocol proceeds as follows (full details are provided in Section 3). Subjects participated in 18 rounds, each requiring them to submit a rank-ordered list (ROL) of schools under uncertainty about their own scores, which determined admission outcomes. At each round, subjects were randomly assigned a color (Blue or Orange), corresponding to high- and low-score distributions, and shown a probability distribution over their scores. They were also shown the deterministic school cutoffs. School payoffs were positively correlated with cutoffs, and three types of cutoffs were used (capturing varying degrees of competitiveness). Four information treatments were implemented: (1) Control, showing only the score distribution; (2) Probability, adding for each school the probability of scoring above its cutoff; (3) Composition, providing simulated enrollment shares by color given truthful behavior; and (4) Real Composition, using the actual choices from the Composition treatment to calculate enrollment shares. No feedback was given across rounds, isolating between-round information effects.

For most rounds, subjects were constrained: they could only submit a ROL with a limited number of schools. First, this constraint mirrors real-world policies such as

those in New York City, where students are allowed to rank only 12 schools despite the existence of hundreds of options. Second, this constraint forces students make a selection, thus making self-selection effects more salient. While the literature provides clear guidance in some cases on how to rank selected schools (e.g., truthfully under DA—see Haeringer and Klijn (2009)), much less is known about how students choose which schools to include in their ROLs, particularly when information is incomplete or framed differently (see also Coles and Shorrer (2014)).

Critically, the information used in both the probability and composition treatments is derived from the same underlying data: score distributions and cutoffs. Yet, by framing this data differently, we observe markedly different behavioral responses.

Our main finding is a strong asymmetry in how subjects react to different types of information. Advantaged (Blue) students respond significantly to both ex-ante and ex-post information, while disadvantaged (Orange) students show weaker responses, particularly to composition information.[3] This asymmetry also manifests in the direction of the responses. Probabilistic (resp. composition) information makes Blue students less (resp. more) ambitious, while for Orange students the effects are opposite. Orange students (weakly) target more demanding schools with probabilistic information (and less demanding schools with composition information. It is only when schools cutoffs are lenient that the treatment effects for orange students becomes similar to the one observed for blue students. Overall, we observe a complex interplay between the degree of school competitiveness (as captured by cutoff levels) and the type information given to the subjects, suggesting that information policy should depend on the targeted population. We also find that on average orange students take more time than blue students to make their choices, indicative of a more

[3]Because each subject was randomly assigned a color (Blue or Orange) in every round, it would be inaccurate to speak of "Blue subjects" or "Orange subjects." Instead, we use the expressions "blue student" and "orange student" to refer to a subject's temporary role in a given round. Throughout the paper, statements such as "blue students select higher-ranked schools" should be understood as "the same subjects select higher-ranked schools when assigned Blue compared to when assigned Orange."

complex task.

Importantly, ex-ante information tends to reduce segregation: it makes the ROLs of advantaged and disadvantaged subjects more similar. In contrast, ex-post composition information tends to increase polarization, as subjects appear to use it to align their choices with those of their own type.

These results highlight a complex interaction between student type, information framing, and the competitive structure of the school market. They suggest that the design of information policies in school choice systems is more delicate than it may initially appear. While well-intentioned, providing certain types of information may reinforce existing disparities or exacerbate segregation if not carefully tailored to the target population.

Related Literature. Our paper contributes to two main strands of literature. First, we add to the literature on information interventions in school choice, motivated by the widespread mismatch between students' academic qualifications and the schools to which they apply, often termed "academic undermatch" by Smith et al. (2013). This phenomenon is especially prevalent among disadvantaged students, as documented in the context of U.S. college admissions both in a single-year census of applicants (Hoxby and Avery, 2013) and in a nationally representative dataset over time (Smith et al., 2013). Similar patterns are observed in public school choice in other contexts, such as applications to the selective Specialized High Schools in New York City (Corcoran and Baker-Smith, 2018) and, more recently, to senior high schools in Ghana (Ajayi, 2024). The disadvantages that lead students to self-select into less selective schools include coming from a low-income family (Corcoran and Baker-Smith, 2018; Hoxby and Avery, 2013; Smith et al., 2013), being from a rural area or a first-generation college student (Smith et al., 2013), or attending a low-performing junior high school (Ajayi, 2024). More generally, Ainsworth et al. (2023) show in the context of Romanian high school admissions that families could have chosen schools with higher value added but left this "on the table."

A growing body of research points to the lack of accurate information about school

characteristics as a possible explanation for this phenomenon. Yet, the evidence on the effectiveness of information interventions is mixed. In public school choice, the information typically provided includes schools' test scores (Hastings and Weinstein, 2008) or value added (Ainsworth et al., 2023). In the U.S. context, both natural and field experiments in Hastings and Weinstein (2008) show that providing this information increased the likelihood that low-income families chose better schools. By contrast, Ainsworth et al. (2023) find only moderate effects of providing value-added information in Romania and estimate that the lack of information explains at most a quarter of why families chose academically suboptimal schools. In college admissions, interventions often include not only academic traits but also financial components such as net price, which are central to enrollment decisions. Despite promising early evidence (Hoxby et al., 2013; Hoxby and Turner, 2015), larger-scale versions of such interventions often proved ineffective. Both Hyman (2020) and Gurantz et al. (2021) find overall null effects. Moreover, Hyman (2020) provide tentative evidence that, rather than correcting misaligned choices, students who responded to the intervention may have been less likely to persist once enrolled. These findings suggest that while information interventions can influence school choice, their effectiveness depends on the type of information provided, the decision context, and the format of delivery.

Our paper addresses self-selection by focusing on information about admission chances, which has received relatively little attention as a primary research question, even though it has appeared as a component in other interventions. For example, Hastings and Weinstein (2008) provided some students with "odds forms" that included both school performance and prior admission rates, but found no significant effect of this treatment. Similarly, Ajayi et al. (2017)'s RCT in Ghana included prior cutoffs in a broader information intervention, but their main focus was on the target population. These studies show that while admission chance information has been present in past interventions, its effect and presentation have not been studied in isolation. Our contribution is to disentangle the effect of admission chance information

and examine how its framing influences student choice.

The study closest to ours is the field experiment and subsequent large-scale implementation in the Chilean college admission system by Larroucau et al. (2025). The authors classified mistakes made by participants in the mechanism and found that payoff-relevant errors about admission probabilities—under- and over-confidence—were especially widespread. Two of their treatments provided personalized information on admission chances for schools listed on students' initial ROLs: T2 included previous score cutoffs, and T3 combined cutoffs with warnings if the probability of admission or assignment was low. Both treatments induced students to adjust their ROLs, but these adjustments did not lead to better assignment outcomes for students who only received cutoff information.

A key difference between our study and theirs is the setting. In Chile, cutoffs and warnings were based on actual early applications, whereas in the context we emulate, students' own scores are unknown at the time of ROL submission, making such interventions infeasible. Instead, we focus on the framing of information: our control treatment resembles their T2 (cutoff scores only), while our other treatments provide admission probability information directly or indirectly via composition data. Our results therefore complement theirs by exploring whether improvements over cutoff-only information are possible when "real-time" information cannot be provided.

Second, our paper contributes to the experimental literature on school choice. Preference misrepresentations in strategy-proof mechanisms such as DA have been repeatedly observed both in laboratory settings and in the field.[4] Although our focus is not on misrepresentation per se, we also observed it in our experiment, in the form of ROLs shorter than the maximum allowed and inversions (i.e., ranking higher-payoff, more selective schools below lower-payoff, less selective schools). One possible explanation for such behavior is mistakes in assessing admission probabilities. Among experimental papers exploring this issue, Rees-Jones et al. (2024) is

[4]For an excellent survey of this literature, see Rees-Jones and Shorrer (2023). See also Hakimov and Kübler (2021).

particularly close to us. Their first experiment, in a setting that abstracts away from strategic concerns, documents evidence of correlation neglect: subjects submitted overly aggressive ROLs in scenarios with correlated admission probabilities. This is consistent with our recorded inversions, where a more selective school is ranked below a less selective one.[5] While Rees-Jones et al. (2024) investigated debiasing interventions in a second experiment, some of the information they introduced was already part of our baseline instructions, which allows us to focus on the framing of additional treatments. In addition to highlighting admission probability, our study contributes by examining the heterogeneous responses of advantaged and disadvantaged students and the resulting equilibrium outcomes, such as segregation—phenomena not covered by Rees-Jones et al. (2024).

Other experimental studies have examined the role of information, but, to our knowledge, none have tested the effect of providing direct admission probability information. For instance, Chen and He (2021) study the choice of costly information acquisition in both DA and IA. Their treatments involve acquiring information about one's own value for schools and about the values of others, but interdependence across values is ruled out by design. Likewise, Basteck and Mantovani (2023) provide information on other participants' choices (not outcomes) from a previous round, focusing on IA. In both cases, the provided information is indirectly relevant to admission chances but requires additional assumptions about opponents' behavior. By contrast, our non-strategic setting allows us to study the effect of probability framing alone.

2 Hypothesis on behavior and outcomes

There is no unambiguous way to define self selection. In its minimal interpretation in a school choice context, self selection is simply a synonym for not including cer-

[5]Note, however, that in their setting schools' payoffs and selectiveness were not perfectly correlated as in ours.

tain schools in one's submitted ROL. Since most of our experiment will consist of *constrained* choice, there will necessarily be self selection in our experiment. What we are more interested in our analysis is the extent of self-selection, whether the self-selection is detrimental to the students' final assignment, and its impact on schools' composition.

However, quantifying self-selection is even more difficult because of the multi-dimensionality of our problem. For instance, there is no unambiguous way to compare a student whose rank order list contains, say, her first, 3rd and 5th choice, with another student whose list contains her 2nd, 3rd and 4th choice. For this reason a significant part of our analysis will essentially focus on the structure of subjects' submitted lists. Some of the metrics we will consider are:

- The rank in the preferences of the school put first/second/third in the submitted rank order list.
- The average rank (in the preferences) of the schools put in the submitted rank order list.
- The difference between the ranks (in the preferences) of the first and second (second and third, first and third) schools put in the submitted rank order list.

Besides the structure of subjects' choices we will also consider the outcomes, that is, the value of the school they would eventually be matched to given their submitted rank order lists. The analysis of outcomes will consist of simulating the matching algorithm given subjects' choices in order to determine their expected payoff (which will also be used to determine subjects' payments in the experiment). It is important to distinguish strategies from outcomes because two different strategies may lead similar expected payoffs. Also, considering outcomes will also permit us to measure the impact of subjects' selection, that is, understand to what extent subjects choices are detrimental. Regarding outcomes the main metrics will consider are:

- The payoff loss between the optimal strategy (i.e., the rank order list that maximizes the expected payoff) and the rank order lists submitted by the

subjects. Using this metric will allow us to measure the impact of selection on individuals' welfare.

- Schools' compositions, i.e., how types are distributed across schools. This metric will allow us to measure the impact of selection on, for instance, diversity.

As we have already explained, we will consider three treatments:

- **Control group**: subjects are only given the cutoffs for each school (the cutoff is increasing with the value of a school);
- **Admission group**: Subjects are given the cutoffs for each school and the unconditional probability to be admitted to each school, depending on their type.
- **Composition group**: Subjects are given the cutoffs for each school and the percentage of each type admitted to each school.

The control group will allow us to see whether additional information (about admission probabilities or composition statistics) can mitigate or intensify selection. Comparisons between the admission group and the composition group will permit us to compare impact of the nature of uncertainty (ex-ante or ex-post) on self-selection.

There are several major hypotheses that our experiment aims at testing.

2.1 Hypothesis ♯1

Our first conjecture is that providing additional information about their chances at each school (whether "likelihood" or "past outcomes") will decrease the average payoff, that is, subjects in the composition and admission groups will lower average payoffs than for subjects in the control group.

Although non-intuitive, this conjecture is supported by a series of previous experiments that started with the contribution of Pais and Pintér (2008), who observed that the subjects, in a context of school choice mechanism like ours, tend to be more strategic when they are given more information.

2.2 Hypothesis ♯2

Our second conjecture concerns the comparison between the probability and composition treatments. Recall that in the probability group subjects are given information about their chances that are framed as ex-ante chances (i.e., probabilistic) and the composition group frame this information as a ex-post (i.e., statistical).

We expect subjects to adopt a strategy that is akin to having a higher degree of risk aversion when presented a probabilistic information. In other words, we expects a higher likelihood that subjects select medium or low payoff schools in the probability treatment than in the composition group. A milder effect in the composition treatment can be interpreted as a value of role model signaling: Statistics showing that some students in a group (low or high) were admitted in a school can be read by subjects as some "proof" that it is indeed feasible to be admitted in a particular school.

2.3 Hypothesis ♯3

Our third hypothesis is that being of low type has a higher negative impact on one's outcome. More precisely, we conjecture that when subjects are assigned the low type their choices will entail in lower average payoffs than when being high type (this is a within subject analysis). The rationale behind this hypothesis is that since the probability to be admitted to high payoff schools is lower for low types than for high types, low type subjects will select on average less preferred schools than the high types. As a consequence, the average payoff will be lower.

2.4 Hypothesis ♯4

For each treatment (control, composition and probability) and for each type (low and high type) we expect that subjects with a higher degree of risk aversion and lower math literacy to select on average more schools will low payoffs and that the average payoff will be decreasing with the degree of risk aversion. Assuming that participants

can develop own strategy based on a combination of "strategy" and "heuristics," low math literacy and high risk aversion would increase reliance on the latter.

3 Experimental Design

3.1 Overview

The experiment consisted of four treatments, each with a similar structure and set of tasks. Each treatment included three parts: (1) instructions, comprehension questions, and trial rounds; (2) multiple rounds of school choice; (3) math and risk-aversion tasks, followed by feedback. The experiment was conducted online using Qualtrics. Subjects who completed it received a $4 participation fee.[6]

The core of the experiment consisted of 18 rounds where subjects submitted a rank-ordered list (ROL) of schools from a set of 8, labeled A through H. Payoffs for each school were fixed: $8 for school A, $7 for school B, ..., $1 for school H, and $0 if unmatched.

An important feature of the experiment is that subjects received no feedback after each round. At the end of the experiment, one round was selected at random, and a school match was determined based on the subject's ROL and the parameters of that round. More details are provided in Section 3.2.

The final part of the experiment included a lottery valuation task and a timed arithmetic task. Subjects had to complete both task, but only had a 10% chance of being eligible for an extra bonus based on one of the two tasks (which was chosen at random).

[6]The first three treatments were conducted on December 1, 2024; the fourth (and final) treatment took place on February 23, 2025. A total of 272 subjects started the experiment, but only 205 completed it. For the first three treatments, a $3 participation fee was announced (with an expected duration of 15 minutes). On average, subjects took about 30 minutes to complete the experiment. To comply with Prolific's minimum hourly payment, an extra bonus of $0.86 was given ex post to participants in the first three treatments. For the fourth treatment, the expected duration on the Prolific announcement was updated to "20-30 minutes," and no additional bonus was required.

In the lottery task, subjects valued 10 binary lotteries (e.g., 5% chance of \$8 and 95% chance of \$1), following Bruhin et al. (2010). The lottery bonus was calculated using the Becker-DeGroot-Marschak (BDM) method: one lottery was selected, a random price drawn, and if the subject's valuation exceeded the price, the lottery was played; otherwise, they received the random price.

In the arithmetic task (lasting 30 seconds), subjects solved up to 10 calculations of the form $6 + 5 - 1 + 9$. Subjects eligible for the bonus received \$1 for each correct answer.

After completing the tasks, subjects answered a few questions and were given the opportunity to leave comments. Final payoffs were then displayed and subjects were redirected to Prolific to validate their participation.

3.2 School Choice

The matching mechanism involves comparing subjects' scores to fixed school cutoffs (all integers between 0 and 100). A subject was admitted to a school if their score was greater than or equal to that school's cutoff. Thus, school choice in this experiment boiled down to a decision problem, and not an interactive matching game. This design was motivated by two considerations. First, prior work (e.g., Chen and Sönmez 2006; Calsamiglia et al. 2010) shows that capacity constraints affect self-selection. Removing this element allows us to isolate the effect of information. Second, Prolific experiments are asynchronous; using non-interactive matching ensured that subjects could be given immediate payoff feedback at the end.

In each round, subjects were assigned either the color *Orange* or the color *Blue*. To each color corresponds a different probability distribution over scores. For all treatment, subjects were given for each school the probability that school is the highest ranked school (i.e., the school that gives the highest payoff). That is, subjects were given for each school the probability that their score would be greater than or equal to that school's cutoff but (strictly) lower than the next school in the payoff ranking. Subjects were shown those probabilities for each color. Density formulas

for the Blue and Orange distribution are

$$f(x) = \begin{cases} 0.0002x & \text{if Orange} \\ 0.02 - 0.0002x & \text{if Blue} \end{cases}$$

In other words, subjects had higher expected scores under Blue than under Orange. Each subject faced the Blue distribution in 9 of the 18 rounds.

3.3 Treatments

Four different information treatments were implemented in the experiment, each designed to shape how subjects formed expectations and made school choices under uncertainty. These treatments varied in the type and framing of information provided, distinguishing between ex-ante probabilistic information and more contextual, outcome-based information that resembles peer guidance or social comparison.

In the *Control* treatment, subjects were given minimal guidance: they could only see the probability distribution of their own score, with no additional cues about their chances of admission or how others might behave.

The *Probability* treatment added a layer of ex-ante information. In addition to their own score distribution, subjects were shown, for each school, the probability that their score would meet or exceed the cutoff. This treatment framed the decision as one involving statistical odds or "chances," helping subjects better gauge their likelihood of admission based on their own uncertainty.

The remaining two treatments, *Composition* and *Composition 2*, introduced a qualitatively different type of information. Instead of focusing on the subject's own chances, these treatments conveyed a sense of who typically gets into each school, effectively providing a form of peer-based reference or social composition signal.

In the Composition treatment, this information was derived from simulated truthful strategies: for each school, subjects saw the proportion of admitted students who were Blue or Orange under the assumption that all students applied truthfully. [7]

[7]Subjects were told: "*These numbers are determined when students are admitted to the best*

In contrast, the Composition 2 treatment relied on real behavior: the same compositional percentages were calculated using the actual ROLs submitted by participants in the Composition treatment. [8]

Together, these two composition treatments provided a kind of ex-post information (either based on modeled truth-telling or actual peer behavior) potentially shaping subjects' strategies through identification, imitation, or a desire to match with similar peers.

3.4 Schools' Cutoffs

To capture a range of admission environments, we introduced variation in the competitiveness of schools by using three distinct cutoff profiles: Balanced, Tight, and Loose. These configurations were fixed parameters of the experimental design and served to generate different strategic environments while maintaining the same payoff structure.

The Balanced profile served as a baseline: cutoff scores gradually declined from top to bottom-ranked schools. In this scenario, the most selective schools (A, B, C) were competitive, but not prohibitively so, while lower-ranked schools were broadly accessible.

The Tight profile introduced a highly competitive environment at the top. Here, the cutoffs for the top-ranked schools were significantly raised, making admission to high-payoff options more elusive. This setup was designed to test whether subjects would respond by shifting their attention toward safer, lower-ranked schools, even when the payoff gradient remained unchanged.

Conversely, the Loose profile relaxed the admission thresholds across the board, particularly at the top. In this setting, even the most valuable schools were within

possible school given their scores." An example clarified that if a school had 19% Orange and 81% Blue students, "*Among those admitted (but not to better schools), 19% are Orange and 81% are Blue.*"

[8]Subjects were told: "*These numbers were obtained using the choices of previous participants facing the same decisions.*"

easier reach. The goal was to observe whether subjects would take advantage of the increased accessibility, perhaps submitting more ambitious ROLs.

Subjects were informed that cutoffs could vary from round to round, although the exact profiles were presented in each round without any label or additional explanation. The three configurations are summarized in Table 1:

School	**Balanced**	**Tight**	**Loose**
A	88	96	75
B	75	90	53
C	63	83	38
D	50	74	26
E	38	62	17
F	25	47	10
G	13	25	4
H	0	0	0

Table 1: Cutoffs by school and cutoff type

These varying cutoff structures allowed us to test whether and how subjects adapted their application behavior to changes in competitiveness, and whether information treatments interacted with these structural conditions.

3.5 Round Design

Each subject completed 18 decision rounds in the experiment, with each round varying along three key dimensions: the type of cutoff structure used (Balanced, Tight, or Loose), the score distribution assigned to the subject (Blue or Orange), and the length constraint imposed on the ROLs' length (either 3 schools (constrained) or 8 schools (unconstrained)).

The design ensured that each subject faced a wide variety of strategic environments. In the constrained condition (ROL length = 3), each combination of cutoff

type and color appeared twice, leading to $2 \times 3 \times 2 = 12$ rounds. In contrast, for the unconstrained case subjects were given each cutoff-color combination only once, yielding 6 additional rounds.

This structure ensured coverage of all possible combinations while limiting repetition, allowing for within-subject comparisons. The full list of round configurations is provided in Table 1 of the Data Appendix.

The inclusion of unconstrained rounds served two purposes. First, it broke the potential monotony of repeated constrained decision-making. Second—and more importantly—it provided a benchmark for rationality. Given the simplicity of the matching mechanism, truthfully ranking all 8 schools in payoff order is the most natural and optimal strategy in the unconstrained case. Any deviations from this benchmark can thus be interpreted as mistakes, misunderstandings, or behavioral noise.

Subjects were presented with these 18 rounds in a random order, ensuring that no particular sequence of environments could systematically affect outcomes. For example, one subject might begin with a constrained round under the Tight cutoff and Blue color, while another might start with an unconstrained round under the Loose cutoff and Orange color. This randomization adds robustness to the identification of treatment effects.

3.6 Recruitment

Subjects were recruited through the online platform Prolific. Participation was open to U.S. residents aged 18 or older, with no additional eligibility restrictions.

A total of 271 individuals began the experiment. Of these, 205 completed all parts, including the comprehension questions, school choice rounds, and post-experiment tasks. Only the subjects who passed the comprehension check were included in the our analysis. This left us with a final sample of 142 participants. The sample was evenly distributed across treatments: 35 subjects in both the Control and Composi-

tion treatments, and 36 in both the Probability and Composition 2 treatments.[9]

Participants were compensated based on both participation and performance. The average payment across all 205 subjects was \$7.10, with earnings ranging from a minimum of \$3.86 to a maximum of \$17.22.[10]

4 Analysis of Choices

When choice is constrained, subjects must decide both which schools to include in their ROLs and the order in which to rank them. This section analyzes both aspects.

4.1 Choice Structure

Blue subjects, having higher expected scores, should be more likely to select high-payoff schools. To analyze this, we compute the average payoff rank of schools in each submitted ROL. For instance, if a ROL contains A, C, and E, that is, the schools ranked 1st, 3rd, and 5th in the payoffs, then the average rank of that ROL is $(1 + 3 + 5)/3 = 3.0$. Since we are here only interested in understanding how the environment affects school selection, we ignore when computing those average ranks the inversions in the rankings. So, ROLs like A, C, E and A, E, C are treated equally.

Figure 1 shows average ranks by treatment, cutoff type, and ROL length. Lower averages imply selection of higher-payoff schools. As expected, Orange subjects generally choose lower-ranked schools.[11]

Comparisons between colors show that the difference between are statistically significant in all constrained cases—see Table 6 in the Web Appendix. For the un-

[9]Subjects were given up to three attempts to correctly answer the comprehension questions. Those who failed all three were still allowed to proceed through the experiment and received full payment, but their data were excluded from the analysis.

[10]These figures includes participation fees, the performance-based bonuses, as well as adjustments made to meet Prolific's minimum hourly wage requirements for the Control, Composition, and Probability treatments.

[11]Table 5 in the Web Appendix gives the average ranks for each treatment and cutoff-color case.

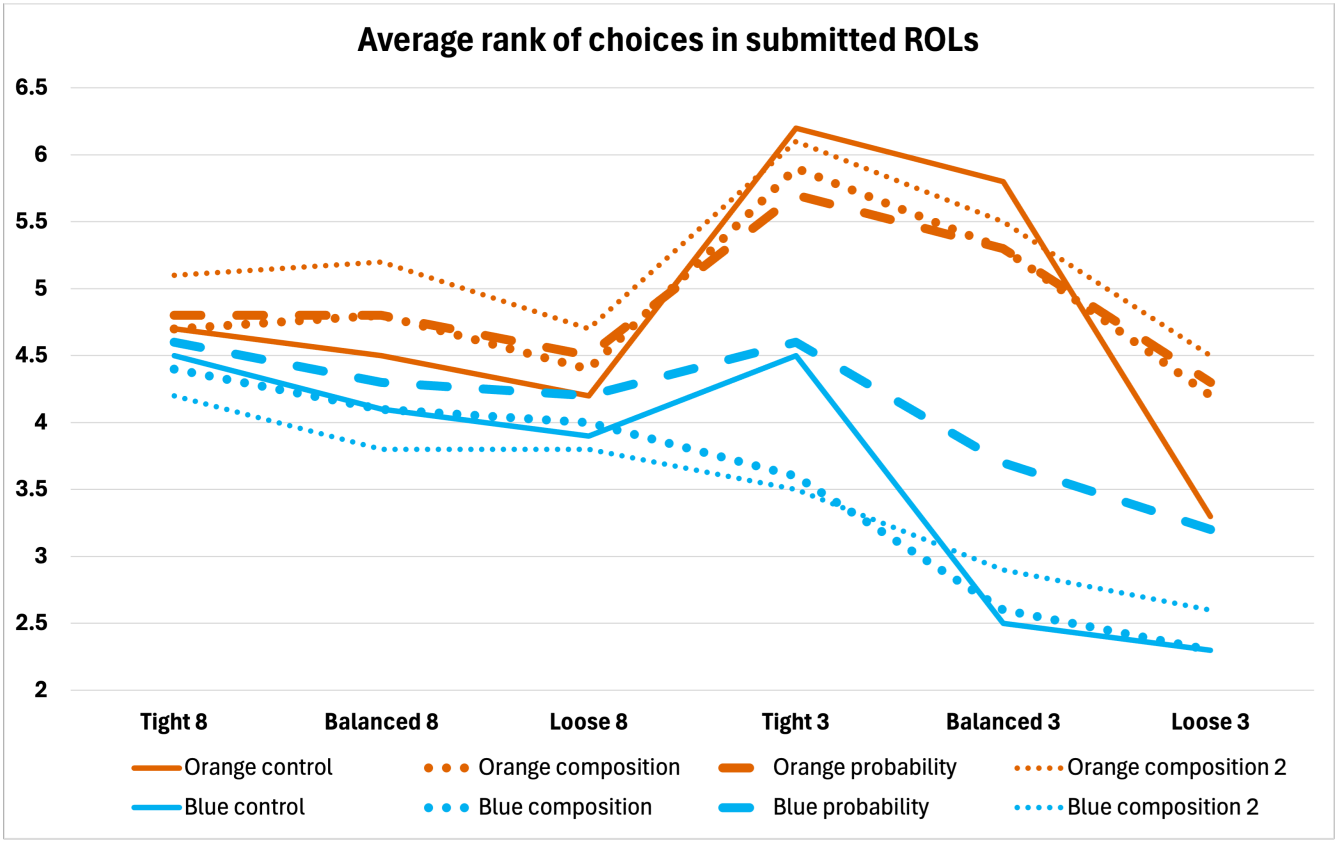


Figure 1: Average rank of schools in submitted ROLs

constrained cases, there is no significant difference between Blue and Orange students in the Control treatment (tight and loose cutoff, with p-value of 0.27 and 0.14, respectively), and in the Composition treatment with tight cutoff (p-value of 0.12). For all the other cases, the difference is significant. In unconstrained rounds, the optimal strategy is to rank all 8 schools, leading to an average rank of 4.5. Deviations from this value stem from incomplete ROLs—about 27% of unconstrained ROLs omit at least one school (Table 1).

Subjects are not only sensitive to their assigned color at each round, but also to the cutoffs. Average ranks for tight (resp. balanced) cutoffs are higher than for balanced (resp. loose) cutoffs. Table 2 confirms subjects respond to cutoffs at each

round. Except for a few cases in the unconstrained cases, differences between tight, balanced, and loose cutoffs are significant.

The comparison between treatments is of particular interest, as it will shed light on whether providing subjects with additional information affects their choices. Data on average ranks suggests a striking difference between treatments. First, the Composition data seems to have opposite effect on blue and orange students when compared to the control treatment. Orange students become more cautious (the average ranks increase), while blue students become more ambitious, selecting higher ranked schools in their ROLs. The effect is opposive for the Probability treatments for blue students. Compared to the Control treatment, blue students are more cautious when being presented information about their chances of access to schools. For orange students, the effect of the Probability treatment is more subtle. When choice is unconstrained it makes them more cautious, but more ambitious in the constrained case.

In short, data on average ranks suggests a complex interplay between treatments, colors and cutoff types. To better capture the relations between those variables we run the following regressions, for the unconstrained and constrained cases, with the Control treatment, blue, and balanced cutoff as the baseline,

$$\begin{aligned}\text{AverageRank}_{i,r} = \beta_0 &+ \sum_t \beta_t \text{Treatment}_t + \beta_{\text{Orange}}\text{Orange} + \sum_c \beta_c \text{Cutoff}_c \\ &+ \sum_t \left(\beta_{t\times\text{Orange}}\text{Treatment}_t \cdot \text{Orange} + \beta_{t\times c}\text{Treatment}_t \cdot \text{Cutoff}_c\right) \\ &+ \sum_c \left(\beta_{\text{Orange}\times c}\text{Orange} \cdot \text{Cutoff}_c\right) \\ &+ \sum_t \sum_c \left(\beta_{t\times\text{Orange}\times c}\text{Treatment}_t \cdot \text{Orange} \cdot \text{Cutoff}_c\right) + \alpha_i + \varepsilon_{i,r}\end{aligned} \tag{1}$$

where,

- $\text{AverageRank}_{i,r}$ is the average rank submitted by subject i at round r; β_0: Intercept (the average rank for the Control treatment, blue color, and balanced

Tight v. Balanced

	Control	Probability	Composition	Composition 2
Orange 8	0.19	1	0.55	0.75
Blue 8	0.035	0.016	0.064	0.02
Orange 3	0.0017	0.0038	0.00041	4.1×10^{-05}
Blue 3	4.8×10^{-14}	1.3×10^{-06}	1.2×10^{-06}	7.8×10^{-06}

Tight v. Loose

	Control	Probability	Composition	Composition 2
Orange 8	0.0064	0.015	0.14	0.024
Blue 8	0.0055	0.01	0.015	0.056
Orange 3	6.8×10^{-26}	2.2×10^{-12}	9.3×10^{-15}	6.7×10^{-15}
Blue 3	1.1×10^{-18}	4×10^{-12}	3.6×10^{-11}	7×10^{-07}

Balanced v. Loose

	Control	Probability	Composition	Composition 2
Orange 8	0.0064	0.001	0.023	0.0047
Blue 8	0.28	0.88	0.072	0.9
Orange 3	4.6×10^{-19}	1.1×10^{-07}	1.8×10^{-09}	5.9×10^{-07}
Blue 3	0.065	6.2×10^{-05}	0.0069	0.0032

Table 2: p-values for comparison of average ranks across cutoffs

cutoff).

- Treatment_t is a series of dummry variables variables indicating whether subject i was assigned to treatment t, where $t \in \text{Composition}, \text{Probability}, \text{Composition 2}$.
- Orange is an indicator for whether the subject's color was orange
- Cutoff_c is a series of dummy variables for cutoff type, where $c \in \text{Tight}, \text{Loose}$.
- α_i captures subject fixed effects.

The interaction terms $\beta_{t\times\text{Orange}}$ is to capture the difference in treatment effects for orange and blue students, $\beta_{t\times c}$ for the difference in treatment for tight and loose cutoff (relative to the balanced cutoffs), $\beta_{\text{Orange}\times c}$ captures the color effect under tight and loose cutoffs, and $\beta_{t\times\text{Orange}\times c}$ captures the difference in treatment effect for orange under tight or loose cutoffs.

Regression results are given in Table 3. The most interesting case is for the constrained case, showing a complex interplay between cutoffs, informational treatment, and color. Regarding cutoffs, the regression confirms the preliminary analysis performed earlier. Subjects are significantly less 'ambitious' under tight cutoffs compared to balanced ones. The estimated effect of a tight cutoff is large and highly significant, while loose cutoffs are associated with slightly lower average ranks, though this effect is only marginally significant.

Subject's chances over scores has also a significant effect on their decisions. In the baseline category (blue color, control treatment, balanced cutoff), switching from blue to orange leads to a sharp increase of self-selection. Interestingly, this color effect is moderated by the cutoff: under tight or loose cutoffs, the difference between orange and blue narrows considerably. In particular, the orange effect is reduced by about two points under loose cutoffs, indicating that color matters most when the underlying choice environment is ambiguous, as in the balanced cutoff case.

Treatment effects are also strongly dependent on both color and cutoff. For blue subjects, the Probability treatment significantly increases average ranks, that

is, making subjects less ambitious. In contrast, ex-ante information (Probability treatment) has the opposite effect for orange. Orange students are more ambitious, under both tight and loose cutoffs. The net result is that the Probability treatment harms blue subjects but helps orange ones, particularly when the cutoffs are extreme.

The Composition and Composition 2 treatments show a similar pattern. While their average effects for blue subjects are modest and statistically insignificant, their interaction with cutoff and color reveals a different picture. Under tight cutoffs, both treatments significantly reduce average ranks, and this effect is even stronger for orange subjects.

The results shed light on how different types of informational interventions influence students' school choices, and suggest that such policies may not always work as intended. When choice is constrained, students faced a limited number of options, making their decisions more consequential. Students do not respond the same when receiving probabilistic information. High-scoring students (blue) actually performed worse on average: their submitted rankings led to higher average positions, suggesting poorer outcomes relative to the control group. By contrast, low-scoring students (orange) improved significantly. The same information helped them avoid applying to schools that were likely out of reach and instead prioritize options where admission was more realistic. This divergence highlights that even neutral, objective information can benefit some groups while confusing or deterring others.

A similar pattern appears with the Composition treatment, which gave students information about the percentage of blue and orange students at each school—data that might help them identify with "students like me." While this kind of information is often assumed to improve decision-making, especially among disadvantaged students, the effects were not universal. It helped low-scoring students make better choices under tight cutoffs, but had little or no effect for high scorers. Importantly, this was not driven by any desire to be among peers of the same type: subjects had no incentive to prefer schools with more students like themselves. Instead, the social framing appears to have offered useful cues for students with fewer options. Taken

together, these findings suggest that informational policies must be tailored not just to what information is provided, but to whom and under what circumstances. What helps one group may backfire for another, especially in competitive or constrained environments.

4.2 Rational Behavior

Although ranking by payoff is a weakly dominant strategy, many subjects deviate from it—especially under low expectations. Prior work (e.g., Hakimov and Kübler 2021; Chen and Sönmez 2006; Calsamiglia et al. 2010) shows similar patterns.

In unconstrained rounds, rational ROLs should contain all 8 schools ranked by payoff. Yet, only 71% of ROLs are complete. The average length is about 6.7. For constrained rounds, fewer than 2% of ROLs contain fewer than 3 schools.

We define an "effective ROL" as the subset of a subject's ROL containing only schools for which assignment is possible. For example, if D is ranked above B and the subject's score is sufficient for both, then B will never be assigned, making its inclusion irrelevant. Comparing the difference between the length of the submitted ROL and that of the effective ROL length measures gives the number of ranking inversions.[12]

Table 4 provides results on length comparison between submitted and effective length. As the table shows, blue students make on average fewer inversions. Additional results in the Web Appendix show that inversions are essentially due to colors, and are not related to treatments or subject to some learning effects (e.g., subjects would make more inversions in earlier rounds).

One possible explanation for why orange students make more mistakes is that

[12]The measure constructed that way gives a lower bound on the number of inversion. To see this, consider for instance the ROL (A, C, D, B, E), which gives the effective ROL (A, C, D, E), and thus a difference in the lengths equal to 1. A standard measure in social choice is the Kemeny distance, which counts the number of inversion for pairwise comparison. In this example, there are two pairwise inversions: (B, C) and (B, D).

Table 3: Effect of Treatments, Color, and Cutoffs on Average Rank

	8-school		**3-school**	
Color: Orange	0.419*	(0.021)	3.269***	(<0.001)
Cutoff: Loose	-0.205	(0.276)	-0.212·	(0.069)
Cutoff: Tight	0.410*	(0.030)	1.948***	(<0.001)
Orange × Loose Cutoff	-0.081	(0.742)	-2.226***	(<0.001)
Orange × Tight Cutoff	-0.200	(0.346)	-1.545***	(<0.001)
Blue × Composition	-0.219	(0.425)	0.521	(0.155)
Blue × Probability	-0.160	(0.503)	1.718***	(<0.001)
Blue × Composition 2	-0.940***	(0.003)	0.588	(0.101)
Loose × Composition	0.048	(0.817)	-0.119	(0.488)
Tight × Composition	-0.176	(0.432)	-0.971**	(0.003)
Loose × Probability	0.186	(0.406)	-0.307·	(0.081)
Tight × Probability	-0.122	(0.576)	-1.026**	(0.002)
Loose × Composition 2	0.182	(0.485)	-0.089	(0.587)
Tight × Composition 2	-0.021	(0.933)	-1.265***	(<0.001)
Orange × Loose × Composition	-0.105	(0.718)	1.414***	(<0.001)
Orange × Tight × Composition	-0.121	(0.663)	1.174**	(0.002)
Orange × Loose × Probability	-0.211	(0.458)	1.749***	(<0.001)
Orange × Tight × Probability	-0.087	(0.728)	1.027**	(0.005)
Orange × Loose × Composition 2	-0.352	(0.260)	1.539***	(<0.001)
Orange × Tight × Composition 2	-0.233	(0.431)	1.432***	(<0.001)
Subject Fixed Effects	Yes		Yes	
Observations	852		1,704	
Subjects	142		142	
Clustered SEs	Subject		Subject	
Within R^2	0.219		0.633	

Notes: The dependent variable is the average rank submitted by each subject in each round. All models include subject fixed effects. P-values are shown in parentheses and are clustered at the subject level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, · $p < 0.1$.

Reference categories: Control treatment, blue color, balanced cutoff.

		Tight	**Balanced**	**Loose**
Control	Orange	1.1	1.14	0.51
	Blue	0.71	0.33	0.24
	p-value	0.012	1.14	0.009
Composition	Orange	0.84	0.69	0.59
	Blue	0.33	0.24	0.11
	p-value	0.0003	4.93	7.56×10^{-6}
Probability	Orange	0.68	0.53	0.57
	Blue	0.43	0.58	0.35
	p-value	0.0607	0.768	0.063
Composition 2	Orange	0.57	0.58	0.4
	Blue	0.43	0.32	0.32
	p-value	0.273	0.031	0.474

Table 4: Difference between lengths of submitted and effective ROLs
(p-values rounded to 3 decimals)

they make their choices more hastily. By having lower stakes, the opportunity cost of a suboptimal choice may lead subjects to spend less effort (and thus less time) when choosing their ROLs.

Table 5 displays the average time taken by subjects for each treatment-color-ROL length combination. Overall, the results look mixed, although in 15 out of the 29 cases orange students are taking more time than blue students.[13] Table 6 shows which color takes more time together with the p-value corresponding to t-tests with no difference time-wise between blue and orange students as the null hypothesis. Only in four cases those time differences are not significant. There is no clear pattern

[13]In some cases some subjects took significantly less/more time than the average (e.g., a subject submitting by mistake or taking a break before submitting). To reduce the influence of extreme response times, we excluded outliers by dropping, within each cutoff–color condition, the two fastest and the two slowest observations.

emerging that would explain in which case blue students would take more time. The most salient cases are for the constrained case with tight cutoffs (blue take more time for 3 treatments) and the probability treatment (blue take more time for 3 —out of 6— length-cutoff combination). Those cases are perhaps those where the information given to the blue students looks the less optimistic.

	Control	**Composition**	**Probability**	**Composition 2**
Orange tight 8	15	22	14	22
Blue tight 8	22	17	21	19
Orange balanced 8	20	18	18	19
Blue balanced 8	15	19	16	16
Orange loose 8	20	23	18	17
Blue loose 8	18	20	23	17
Orange tight 3	15	18	16	16
Blue tight 3	20	19	16	17
Orange balanced 3	16	16	14	17
Blue balanced 3	13	19	17	15
Orange loose 3	16	21	15	17
Blue loose 3	13	14	14	13

Table 5: Average time taken to submit

5 Outcome Analysis

5.1 Payoffs

5.2 Segregation

We measure segregation by examining whether Blue and Orange subjects tend to be matched to different schools. Higher segregation implies more divergent school

	Control	Composition	Probability	Composition 2
Tight 8	blue	orange	blue	orange
	1.5×10^{-10}	2.2×10^{-7}	1.5×10^{-10}	2.7×10^{-7}
Balanced 8	orange	blue	orange	orange
	1.7×10^{-13}	0.6	0.82	0.17
Loose 8	orange	orange	blue	orange
	0.0016	2.3×10^{-10}	7.0×10^{-6}	0.00012
Tight 3	blue	blue	orange	blue
	1.3×10^{-14}	8.5×10^{-10}	0.72	0.01
Balanced 3	orange	blue	blue	orange
	8.5×10^{-10}	1.3×10^{-6}	8.4×10^{-14}	8.0×10^{-12}
Loose 3	orange	orange	orange	orange
	2.4×10^{-14}	5.2×10^{-15}	5.8×10^{-7}	2.3×10^{-16}

Table 6: Comparison between colors of average time to submit (p-values)

selections.

We use the Atkinson index (Frankel and Volij, 2011):

$$A = 1 - \left(\sum_{s \in S} \left(t_O(s)^n\right)^{1/2} \left(t_B(s)^n\right)^{1/2} \right)^2 \tag{2}$$

where $t_O(s)$ and $t_B(s)$ are the shares of Orange and Blue students assigned to school s.

Assignments are computed by treating each subject's probabilities as fractional masses:

$$\text{mass}(s, c, f, k) = \sum_{r \in R(c,f,k)} \sum_{i} \text{Prob}(i \text{ assigned to } s \text{ in round } r)$$

Shares $t_O(s, f, k)$ and $t_B(s, f, k)$ are calculated by normalizing over all assigned mass for each color group.

Figure 2 presents Atkinson indices across treatments and cutoff types. Information on school composition increases segregation under tight/balanced cutoffs but decreases it under loose cutoffs. This mirrors patterns in average ranks.

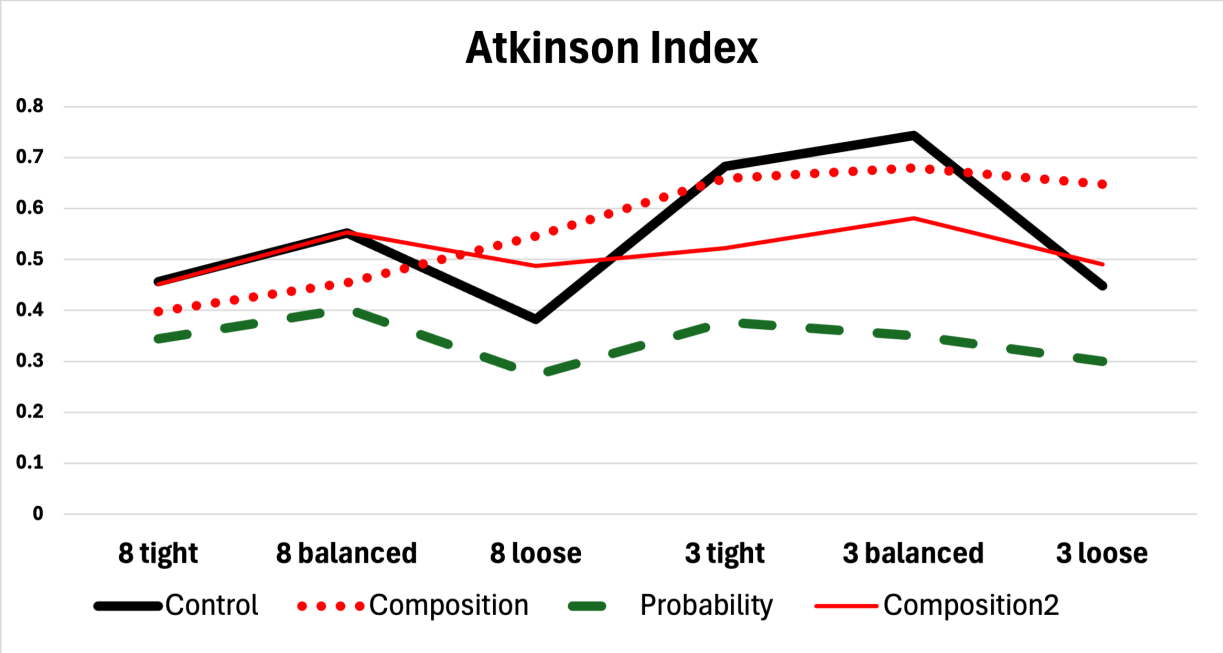


Figure 2: Atkinson index

Probability treatments reduce segregation consistently, by narrowing differences in school selection between groups. This observation is expected, since the analysis of the average ranks done in Section 1.2.1 shows that blue students select lower payoff schools in the Probability treatment, and thus have choices that are more similar than orange students' choices. In contrast, choices are more polarized for the other treatments, which leads naturally to a higher segregation.

To compare treatments we ran permutation tests, for each cutoff and ROL length cases (10,000 iterations). Table 7 summarizes the p-values for those test. Segregation is significantly lower under the Probability treatment in the constrained case, except for when comparing the Probability and Composition 2 treatments for loose cutoffs. For most cases, there is no significant differences exist among Control, Composition,

and Composition 2.[14]

	Tight 8	**Balanced 8**	**Loose 8**	**Tight 3**	**Balanced 3**	**Loose 3**
Cont v. Prob	0.0569	0.0615	0.172	0.0001	< 0.0001	0.0172
Cont v. Comp	0.405	0.194	0.0021	0.838	0.588	0.0011
Cont v. Comp 2	0.968	0.917	0.127	0.197	0.178	0.605
Prob v. Comp	0.414	0.407	< 0.0001	< 0.0001	0.0006	< 0.0001
Prob v. Comp 2	0.0553	0.0205	0.0025	0.0758	0.0142	0.0273
Comp v. Comp 2	0.412	0.0865	0.314	0.182	0.379	0.136

Table 7: p-values to compare Atkinson indices

[14]We ran a similar analysis using Duncan and Duncan's (1955) dissimilarity index in Section 2 of the Web-Appendix. The results are in line with the ones obtained using the Atkinson index.

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Information and Self-selection in School Choice: an Experiment
Web Appendix

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1 Choices

1.1 ROLs' lengths

Table 1 reports the percentage of ROLs submitted by the subjects that are shorter than they should be under rational behavior. It shows a stark contrast between the unconstrained and the constrained case. While nearly all subjects do submit a ROL of length 3 in the constrained cases, about a quarter of the submitted ROLs in the unconstrained case contain fewer than 8 schools.[1]

Table 4 compare across treatments the difference between the lengths of the submitted and effective ROLs. These differences capture the number of inversions that subjects make in their ROLs.

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[1]The average lengths in the unconstrained case are between 6.3 and 7.

Case	Control	Composition	Probability	Composition 2
Orange tight 8	22.9	25.7	30.6	38.9
Blue tight 8	14.3	17.1	22.2	44.4
Orange balanced 8	17.1	25.7	33.3	55.6
Blue balanced 8	20	22.9	27.8	47.2
Orange loose 8	25.7	22.9	19.4	50
Blue loose 8	22.9	25.7	27.8	38.9
Orange tight 3	0	0	0	8.3
Blue tight 3	0	0	0	0
Orange balanced 3	5.7	0	0	5.6
Blue balanced 3	5.7	0	0	2.8
Orange loose 3	5.7	0	0	0
Blue loose 3	5.7	2.9	0	2.8

Table 1: Percentage of subjects with a short ROL (rounded to 1 decimal)

source code: `sub_choices.R`

Case	Control	Composition	Probability	Composition 2
Orange tight 8	6.9	6.7	6.8	6.2
Blue tight 8	7.4	7.2	7.1	5.8
Orange balanced 8	7.3	6.9	6.6	5.4
Blue balanced 8	7.1	7.1	6.7	5.9
Orange loose 8	6.9	6.9	7.2	5.8
Blue loose 8	6.8	6.9	6.9	6.1

Table 2: Average lengths of ROLs (rounded to 1 decimal)

code: `sub_choices.R`

1.2 ROLs' structures

1.2.1 Average ranks

Table 5 gives the average ranks (rounded to the 1st decimal)for each cutoff-color-ROL length case, and for each treatments. Table 6 gives p-values for Welch's test comparison between colors.

Control v. Composition			
	tight	**balanced**	**loose**
orange	1.98 (0.05)	1.33 (0.18)	3.83 (0.00)
blue	5.45 (0.00)	0.73 (0.47)	0.37 (0.71)

Control v. Probability			
	tight	**balanced**	**loose**
orange	1.55 (0.12)	1.12 (0.27)	5.22 (0.00)
blue	0.82 (0.41)	5.83 (0.00)	5.19 (0.00)

Composition v. Probability			
	tight	**balanced**	**loose**
orange	0.61 (0.54)	0.30 (0.77)	1.24 (0.22)
blue	6.35 (0.00)	6.76 (0.00)	5.18 (0.00)

Table 3: t-stats comparing length of ROL across treatments
t-stats and p-values (in parenthesis) rounded to 2nd decimal
source code: `choices.R`

1.3 Rank to top, 2nd, and 3rd choices

The average rank of the schools in the ROLs is not the only possible metric one can use to analyze subjects behavior. Table 7 gives the average ranks of the top, second, and third choices in subjects ROLS, depending on the color, cutoff and treatment. Analysis for those metrics is done only for the constrained cases.

Data shows that for the top, second, and top choices, the average rank is lower for tight (resp. balanced) cutoffs than for balanced (resp. loose) cutoffs for all treatments and colors, except for the 3rd choice for Blue students, where the average rank for balanced cutoffs is lower than for loose cutoffs. Table 8 gives p-values for the cutoff comparisons. Except in a few cases (most notably Blue students for the Balanced v. Loose tests), differences are highly signiticant.

Regarding the comparison between colors, for the top, second, and third choices, Blue students always select schools with higher payoffs (i.e., higher cutoff) than Orange students. Table 10 shows p-values for color comparison.

	Cont v. Comp	Cont v. Prob	Cont v. Comp 2	Comp v. Prob	Comp v. Comp 2	Prob v. Comp 2	
Tight orange	0.0431	0.00206	9.48×10^{-5}	0.304	0.0707	0.442	
Tight blue	0.00566	0.0518	0.0574	0.329	0.368	0.976	
Bal orange	0.43	1.21×10^{-5}	9.82×10^{-5}	0.288	0.539	0.653	
Bal blue	0.815	0.0295	1	0.00321	0.43	0.0295	
Loose orange	0.106	0.675	0.228	0.858	0.171	0.125	
Loose 3 blue	0.106	0.28	0.422	0.00762	0.0247	0.837	

Table 4: Comparison between treatment of difference between submitted and effective ROL lengths (constrained case)

	Tight 8	Balanced 8	Loose 8	Tight 3	Balanced 3	Loose 3
Orange control	4.7	4.5	4.2	6.2	5.8	3.3
Orange composition	4.7	4.8	4.4	5.9	5.3	4.2
Orange probability	4.8	4.8	4.5	5.7	5.3	4.3
Orange composition 2	5.1	5.2	4.7	6.1	5.5	4.5
Blue control	4.5	4.1	3.9	4.5	2.5	2.3
Blue composition	4.4	4.1	4	3.6	2.6	2.3
Blue probability	4.6	4.3	4.2	4.6	3.7	3.2
Blue composition 2	4.2	3.8	3.8	3.5	2.9	2.6

Table 5: Average ranks in ROLs

	Control	Composition	Probability	Composition 2
Tight 8	0.27	0.12	0.071	0.00022
Balanced 8	0.035	0.0024	0.0013	6.8×10^{-08}
Loose 8	0.14	0.037	0.077	0.00039
Tight 3	6.4×10^{-13}	4.7×10^{-18}	1.3×10^{-06}	7.3×10^{-23}
Balanced 3	1.2×10^{-30}	4.5×10^{-23}	4.8×10^{-11}	1.5×10^{-28}
Loose 3	2×10^{-11}	5.8×10^{-21}	4.4×10^{-07}	4.3×10^{-17}

Table 6: p-values comparing average ranks of schools in ROLs between colors

To sum up, the comparison between colors and cutoffs gives essentially similar results than when considering the average rank of all schools in the submitted ROLs. That is, subjects respond rationally to cutoff and color changes. When blue, subjects tend to select higher payoff schools, and similarly when cutoffs are lower.

The treatment comparison also yield similar findings as with the average rank of all schools in the ROLs, although they can give finer insights on how subjects structure their choices. Table 9 gives p-values for treatment comparisons. For the second and third choice, except when cutoffs are loose there are no significan differences between treatments for Orange students. However, differences are more significant for the top choices. Interestingly, except for loose cutoffs additional information (e.g., Composition, Probability, and Composition 2) treatments make subjects selecting lower payoff schools for their top choice compared to the Control treatment.

Blue students are more sensitive to information. Differences between treatments are much more often significant for them. Also, like for the average rank of all schools in the ROLs, a probabilistic information makes subjects more cautious, selecting lower payoff schools. This is the case for the top, second, and third choice.

	Average rank of top choice in ROLs			
	Control	**Composition**	**Probability**	**Composition 2**
Orange tight 3	6.2	5.8	5.1	5.4
Blue tight 3	4.1	2.6	3.5	2.8
Orange balanced 3	5.9	4.9	4.4	4.9
Blue balanced 3	1.7	1.6	2.9	1.9
Orange loose 3	2.7	3.6	3.4	3.6
Blue loose 3	1.4	1.2	2.1	1.8

	Average rank of second choice in ROLs			
	Control	**Composition**	**Probability**	**Composition 2**
Orange tight 3	6.3	6.1	5.8	6.2
Blue tight 3	4.5	3.5	4.8	3.4
Orange balanced 3	5.8	5.5	5.3	5.6
Blue balanced 3	2.4	2.5	3.5	2.8
Orange loose 3	3.3	3.9	4.2	4.6
Blue loose 3	2.3	2.3	3.1	2.5

	Average rank of third choice in ROLs			
	Control	**Composition**	**Probability**	**Composition 2**
Orange tight 3	6	6	6.1	6.4
Blue tight 3	4.7	4.6	5.6	4.4
Orange balanced 3	5.5	5.6	6.1	5.8
Blue balanced 3	2.5	2.8	3.8	2.8
Orange loose 3	3.9	5.1	5.2	5.5
Blue loose 3	3.2	3.3	4.4	3.3

Table 7: Average rank of the top, second, and third choice in ROLs

1.4 Per period analysis

In the experiment subjects submitted ROLS without any feedback, that is, without getting a match given the ROLs they submitted. The main reason for this design is to avoid subjects hedging across periods, and thus making their choices at a given period not only depending on the environement they face (color and cutoff type) but also on past outcomes. One drawback is that this limits learning. It could be, however, that over time subjects become more familiar and more aware that ranking schools in the same order as in the payoffs is a dominant strategy.

A first analysis we performed is with respect to the average ranks statistic. Since for the constrained cases subjects faced each combination of cutoff-color twice, we can test whether for each cutoff-color combination, subjects' average ranks of their schools in their ROLs differ between the first and the second time they faced that combination. Table 11 gives the p-values of Welch's test that compares the 1st and 2nd time subjected faced a cutoff-color case. As the table shows, the null hypothesis that subjects exhibit a constant behavior between the first and the second period cannot be invalidated.

We offer now a series of statistics to analyze the extent of non-rational behavior (i.e., inversions in the ranking of schools) by considering the periods at which the subjects played. Table 12 and Table 13 report the number of inversions for each period for the unconstrained and constrained cases, respectively. Each column corresponds to the number of subjects having at least one inversion at each period. Note that for those two tables the periods are relative in the sense that, say, the 3rd period in the unconstrained case corresponds to the 3rd time the subject was facing an unconstrained case (but it could well be that this corresponds to, say, the 7th period of play in the experiment).

Table 12 and Table 13 suggest that there are no apparent differences between treatments. Table 14 reports p-values for Welch's t-tests that compare the sequence of inversions between treatments.[2]

Several comments are in order. First, there is no apparent learning effect in the experiment. Since the order of cases (cutoff type, color, length of ROL) was random for each subject, the presence of inversions at any period is unlikely to be due to past choices or the set of cases the subjects faced in the previous periods. Second, as Table 14 shows, inversions

[2]For this test we considered the vectors of 18 periods, not distinguishing between the constrained and unconstrained cases.

do not seem to be related to the treatment.

1.5 Average time of decision

Table 15 presents p-values when comparing across cutoff types the average time taken to submit (average times are reported in Table **??** in the main text).

Overall, the results are mixed. The clearest pattern is that tight cutoffs yield students to take more time than under balanced cutoffs in 10 cases (out of 16). Orange students seem also to take more time with balanced cutoffs, suggesting that orange students struggle more with mid-level competitiveness.

2 Seggregation

A popular measure of seggregation is Duncan and Duncan's (1955) dissimilarity index, which is given by

$$D = \frac{1}{2} \sum_{s} |t_O(s, f, k) - t_B(s, f, k)| \tag{1}$$

Table 16 gives the values of the dissimilarity index for each case (ROL lentgh and cutoff type) and treatement. Table 17 gives p-values obtained from permutation tests (with 10,000 replications). In both table values are rounded to the third decimal.

3 Screenshots

This section shows various screenshots for the experiment.

References

Duncan, O. D. and Duncan, B. (1955). A methodological analysis of segregation indexes. *American sociological review*, 20(2):210–217.

	Top choice in ROLs		
	Tight v. Balanced	**Tight v. Loose**	**Balanced v. Loose 2**
Control Orange 3	0.24	1.1×10^{20}	1.4×10^{19}
Control Blue 3	1.3×10^{12}	1.8×10^{17}	0.14
Composition Orange 3	0.00047	6.2×10^{12}	6.9×10^{7}
Composition Blue 3	7.4×10^{5}	3.4×10^{9}	0.022
Probability Orange 3	0.0025	1.9×10^{7}	0.00037
Probability Blue 3	0.028	1.9×10^{7}	1.3×10^{5}
Composition2 Orange 3	0.027	7.9×10^{14}	1.6×10^{6}
Composition2 Blue 3	0.00015	0.00012	0.58

	Second choice in ROLs		
	Tight v. Balanced	**Tight v. Loose**	**Balanced v. Loose 2**
Control Orange 3	0.053	1.5×10^{27}	8.2×10^{17}
Control Blue 3	1.4×10^{15}	4.5×10^{18}	0.3
Composition Orange 3	0.035	4×10^{13}	6.3×10^{8}
Composition Blue 3	2×10^{5}	1.8×10^{9}	0.092
Probability Orange 3	0.044	1.3×10^{9}	2.6×10^{5}
Probability Blue 3	2.6×10^{7}	4.2×10^{11}	0.14
Composition2 Orange 3	0.016	1.6×10^{10}	5.9×10^{5}
Composition2 Blue 3	0.0074	0.00018	0.2

	Third choice in ROLs		
	Tight v. Balanced	**Tight v. Loose**	**Balanced v. Loose 2**
Control Orange 3	0.11	1.6×10^{12}	2.5×10^{7}
Control Blue 3	1.3×10^{10}	1.7×10^{7}	0.013
Composition Orange 3	0.2	0.0015	0.095
Composition Blue 3	1.5×10^{8}	4.8×10^{6}	0.025
Probability Orange 3	0.93	0.0047	0.0023
Probability Blue 3	6.4×10^{7}	0.00011	0.074
Composition2 Orange 3	0.098	0.0058	0.26
Composition2 Blue 3	2.8×10^{7}	0.00014	0.038

Table 8: Comparing across cutoffs ranks of top, second, and third choice in ROLs

Top choice in ROLs						
	C v. M	**C v. P**	**C v. M2**	**M v. P**	**M v M2**	**P v. M2**
Orange tight 3	0.18	0.00096	0.022	0.04	0.32	0.29
Blue tight 3	3.3×10^6	0.061	0.00015	0.002	0.52	0.026
Orange balanced 3	0.0039	1.8×10^5	0.0018	0.12	0.9	0.13
Blue balanced 3	0.67	3.7×10^5	0.33	4.6×10^6	0.16	0.0015
Orange loose 3	0.0012	0.011	0.00055	0.64	0.93	0.57
Blue loose 3	0.03	0.0033	0.068	1.5×10^5	0.0017	0.4

Second choice in ROLs						
	C v. M	**C v. P**	**C v. M2**	**M v. P**	**M v M2**	**P v. M2**
Orange tight 3	0.28	0.025	0.56	0.28	0.57	0.082
Blue tight 3	8×10^5	0.29	3.6×10^5	2.2×10^7	0.66	1.3×10^7
Orange balanced 3	0.28	0.057	0.5	0.4	0.64	0.18
Blue balanced 3	0.6	4.3×10^6	0.12	3.7×10^5	0.31	0.0013
Orange loose 3	0.0085	0.00015	6.7×10^8	0.35	0.013	0.098
Blue loose 3	0.92	3×10^5	0.22	6.6×10^6	0.19	0.0032

Third choice in ROLs						
	C v. M	**C v. P**	**C v. M2**	**M v. P**	**M v M2**	**P v. M2**
Orange tight 3	1	0.75	0.23	0.76	0.25	0.42
Blue tight 3	0.72	0.0078	0.35	0.002	0.55	0.00027
Orange balanced 3	0.86	0.058	0.37	0.095	0.48	0.33
Blue balanced 3	0.46	0.00014	0.45	0.0016	0.98	0.0017
Orange loose 3	3.1×10^5	1.4×10^5	6.1×10^7	0.67	0.19	0.39
Blue loose 3	0.44	2×10^6	0.5	2.8×10^5	0.97	5.8×10^5

Table 9: Comparing across treatments ranks of top, second, and third choice in ROLs

C: Control, M: Composition, P: Probability, M2: Composition 2

	Top choice in ROLs			
	Control	**Composition**	**Probability**	**Composition 2**
Tight 3	9.1×10^{9}	5.8×10^{19}	7.8×10^{7}	4.5×10^{13}
Balanced 3	1.8×10^{27}	1.4×10^{21}	2.1×10^{5}	2×10^{18}
Loose 3	2.3×10^{11}	2.3×10^{18}	1.1×10^{5}	4×10^{09}

	Second choice in ROLs			
	Control	**Composition**	**Probability**	**Composition 2**
Tight 3	5.3×10^{11}	2.6×10^{18}	9.6×10^{5}	3.1×10^{21}
Balanced 3	3.2×10^{25}	2.3×10^{23}	1×10^{10}	5.7×10^{24}
Loose 3	7.5×10^{8}	1.2×10^{12}	2.2×10^{5}	1.5×10^{16}

	Third choice in ROLs			
	Control	**Composition**	**Probability**	**Composition 2**
Tight 3	1.8×10^{5}	5.3×10^{6}	0.088	4×10^{9}
Balanced 3	1.7×10^{17}	2.7×10^{15}	5.1×10^{11}	8×10^{18}
Loose 3	0.0019	1.4×10^{11}	0.0043	2.8×10^{12}

Table 10: Comparing across colors ranks of top, second, and third choice in ROLs

	Control	Composition	Probability	Composition 2
Tight Orange	0.515	0.581	0.851	0.522
Balanced Orange	0.655	0.781	0.978	0.178
Loose Orange	0.357	0.317	0.554	0.857
Tight Blue	0.413	0.112	0.923	0.739
Balanced Blue	0.427	0.353	0.897	0.59
Loose Blue	0.813	0.357	1	0.884

Table 11: p-values (rounded to 3rd decimal) for t-test comparing first and second period average rank.

Treatment	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**
Control	16	22	22	23	14	22
Composition	16	15	18	19	17	15
Probability	15	17	21	19	16	17
Composition2	16	15	14	14	18	18

Table 12: Number of inversions for the 6 periods of unconstrained choice

Treatment	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**11th**	**12th**
Control	17	14	18	17	16	13	17	12	15	13	12	16
Composition	14	14	6	9	11	13	9	13	11	9	9	10
Probability	12	17	12	14	13	15	15	13	9	8	9	14
Composition2	15	10	8	11	11	15	9	8	12	11	9	8

Table 13: Number of inversions for the 12 periods of unconstrained choice

	Composition	**Probability**	**Composition 2**
Control	0.1	0.3	0.08
Composition		0.64	0.78
Probability			0.5

Table 14: Comparing sequence of inversions across treatments

	Tight v. Balanced	Tight v. Loose	Balanced v. Loose
Control Orange 8	0.013	4.30×10^{-6}	0.0044
Control Blue 8	7.30×10^{10}	5.00×10^{-4}	2.30×10^{1}
Control Orange 3	0.38	0.22	0.28
Control Blue 3	2.50×10^{11}	2.60×10^{13}	$1.40 \times 10^{-}$
Composition Orange 8	2.50×10^{-6}	0.033	$6.20 \times 10^{-}$
Composition Blue 8	0.00057	0.075	0.012
Composition Orange 3	2.40×10^{11}	5.00×10^{11}	3.40×10^{1}
Composition Blue 3	0.36	6.90×10^{18}	$1.50 \times 10^{-}$
Probability Orange 8	0.00049	1.30×10^{-9}	0.013
Probability Blue 8	0.00031	0.019	$1.40 \times 10^{-}$
Probability Orange 3	5.90×10^{-5}	0.0097	7.30×10^{1}
Probability Blue 3	0.029	0.00019	$1.00 \times 10^{-}$
Composition2 Orange 8	4.10×10^{-5}	1.80×10^{-6}	0.09
Composition2 Blue 8	0.73	0.001	0.15
Composition2 Orange 3	0.43	1.10×10^{-6}	$2.10 \times 10^{-}$
Composition2 Blue 3	2.70×10^{13}	1.30×10^{11}	0.074

Table 15: Comparison across cutoffs of the average time to submit

	Control	Composition	Probability	Composition2
Tight 8	0.58	0.51	0.56	0.59
Balanced 8	0.64	0.49	0.55	0.66
Loose 8	0.5	0.42	0.66	0.59
Tight 3	0.59	0.55	0.7	0.6
Balanced 3	0.78	0.5	0.74	0.64
Loose 3	0.58	0.42	0.69	0.61

Table 16: Dissimilarity index

	Tight 8	Balanced 8	Loose 8
Control v. Composition	0.767	0.165	0.003
Control v. Probability	0.203	0.015	0.169
Control v. Composition 2	0.850	0.662	0.145
Composition v. Probability	0.312	0.306	0.000
Composition v. Composition 2	0.575	0.035	0.107
Probability v. Composition 2	0.111	0.003	0.011

	Tight 3	Balanced 3	Loose 3
Control v. Composition	0.068	0.608	0.035
Control v. Probability	0.508	0.000	0.012
Control v. Composition 2	0.793	0.058	0.577
Composition v. Probability	0.003	0.001	0.000
Composition v. Composition 2	0.110	0.159	0.252
Probability v. Composition 2	0.331	0.047	0.014

Table 17: p-values for dissimilarity index

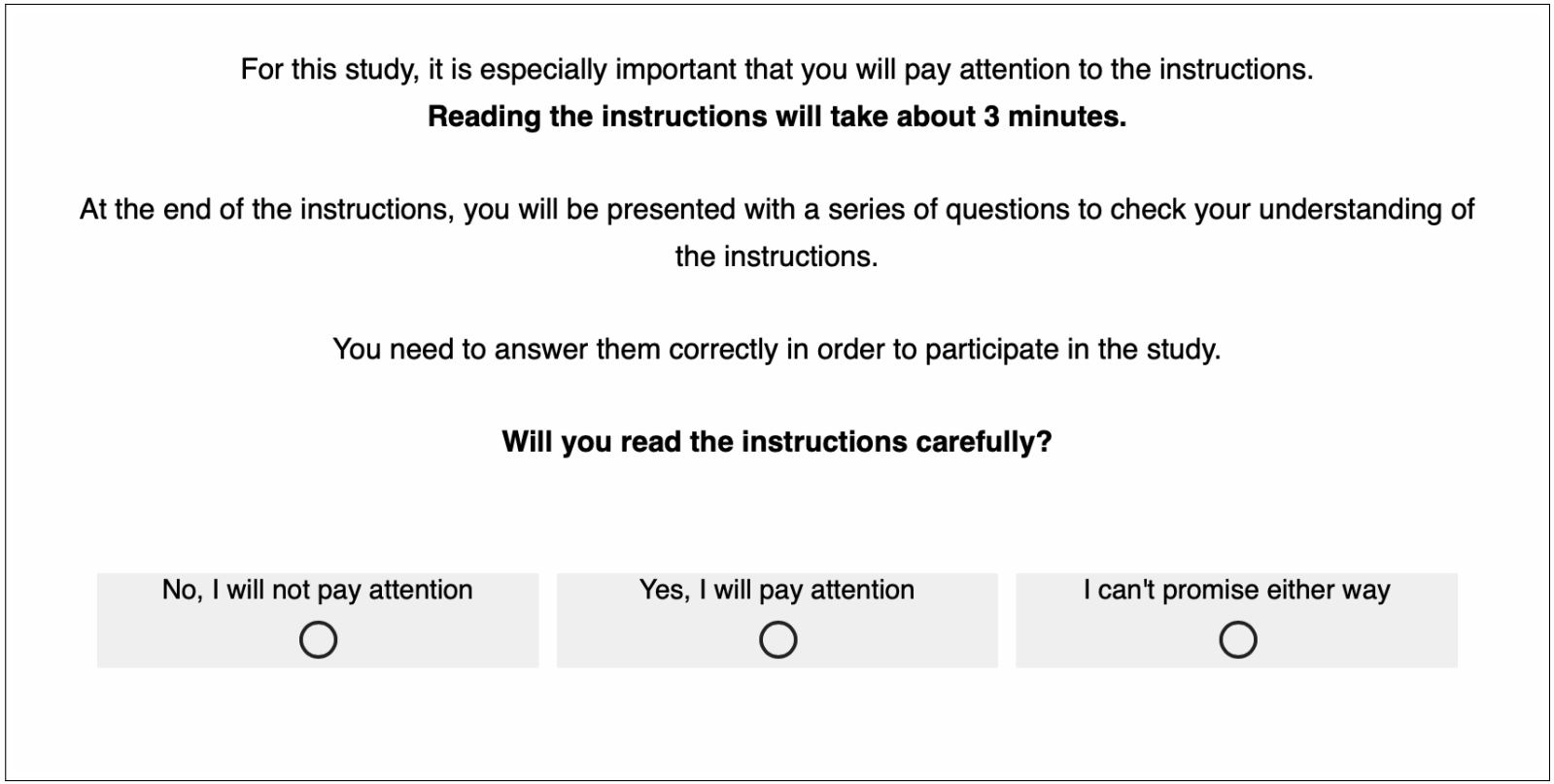


Figure 1: Instructions

General Instruction

This study contains two parts:

Part 1: About 20 minutes (including reading the instructions)
You will mimic a student deciding which school(s) to apply to

Part 2: About 5 minutes (including reading the instructions)
Two short tasks

Upon completion, you will receive:

- a $4 (about £3.23) fee for participating in this survey
- a bonus that depends on the choice you have made in Part 1. That bonus is between $0 and $8 (between £0 and £6.46).
- The chance to get an extra bonus in Part 2, that can be between $0 and $10 (£0 and £8.08)

Figure 2: Instructions

Recap

In this study, you will face a simulation of school applications.

- There are eight schools (A, B, etc.) that differ in their values (points) and their minimal score required for admission.

Your task is to decide to which school to apply and in which order.

Schools admit a student based on his/her/their score.

Rounds will differ based on:

- Schools' admission minimal scores;
- How many schools you can put in your preference list (3 or 8);
- Your color: blue (high chances to get a high score score) or orange (high chances to get a low score).

One Round will be randomly selected for your bonus payment:

- the number of points you collected will become your bonus for this study (1 point = $1 = £0.79)
- Each Round has the same probability of being selected for the bonus.

Figure 3: Instructions

COMPREHENSION QUESTIONS

We want to make sure you understood the main points of the instructions before you start the study.

If you want to read the instructions again, you can find them here: Link to Instructions.

You will be presented with a series of comprehension questions.
You cannot proceed until you answer all of them correctly.

Figure 4: Comprehension message

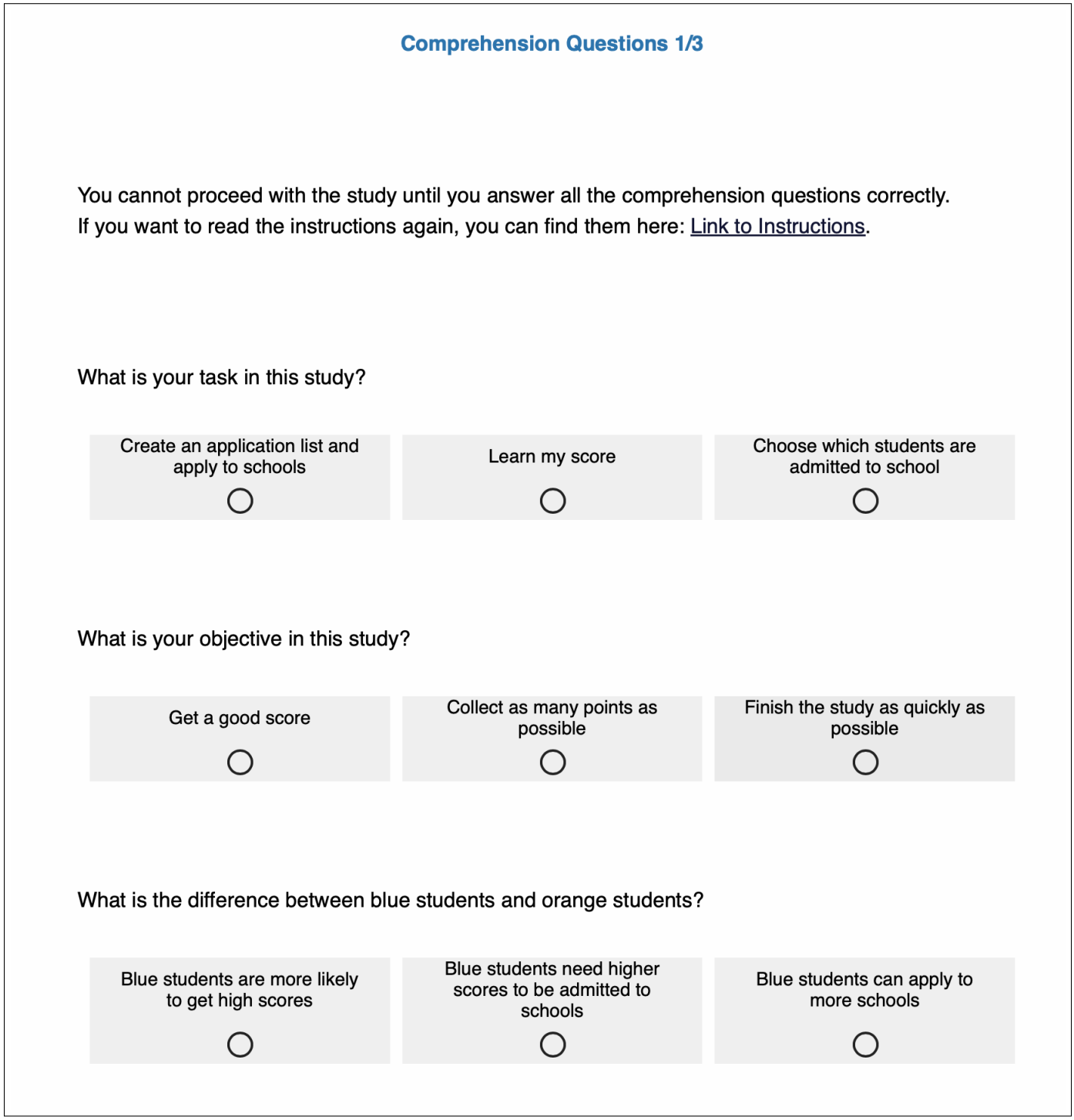


Figure 5: Comprehension question

YOU ANSWERED CORRECTLY - Comprehension Questions 2/3

You cannot proceed with the study until you answer all the comprehension questions correctly.
If you want to read the instructions again, you can find them here: Link to Instructions.

School	Points	Your score needs to be at least equal to
A	8	88
B	7	75
C	6	63
D	5	50
E	4	38
F	3	25
G	2	13
H	1	0

Consider the table above. How many points would you get if you were:
1) admitted to school F? and
2) rejected by all the schools you applied to?

1) three points 2) zero points	1) eight points 2) zero points	1) three points 2) two points	1) eight points 2) two points
○	○	○	○

Figure 6: Comprehension question

School	Points	Your score needs to be at least equal to
A	8	88
B	7	75
C	6	63
D	5	50
E	4	38
F	3	25
G	2	13
H	1	0

Consider the table above. What score is required to be:
1) admitted to school B? and
2) admitted to school D?

1) at least 75 2) at most 50	1) at most 75 2) at most 50	1) at most 75 2) at least 50	1) at least 75 2) at least 50
○	○	○	○

Figure 7: Comprehension question

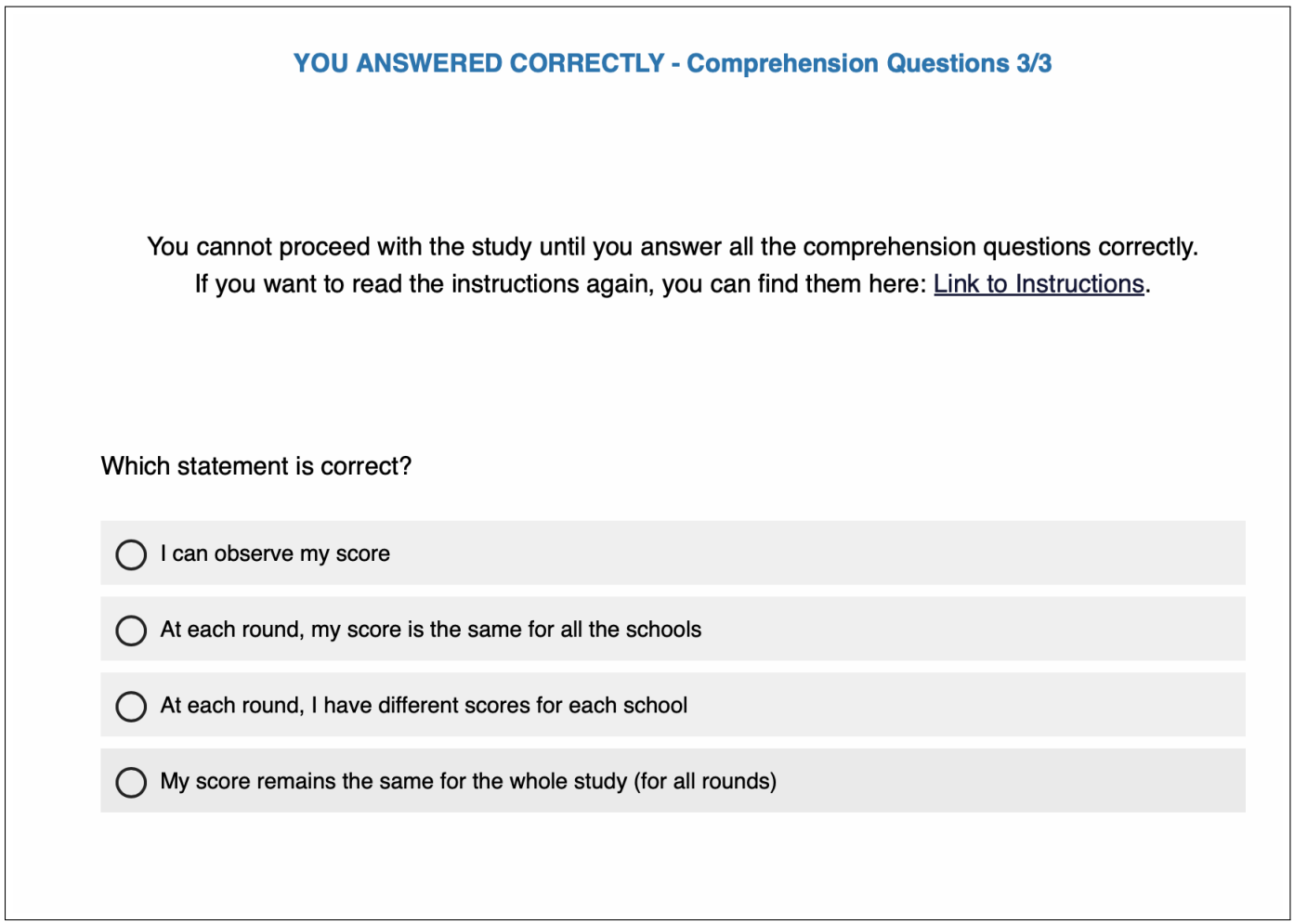


Figure 8: Comprehension question

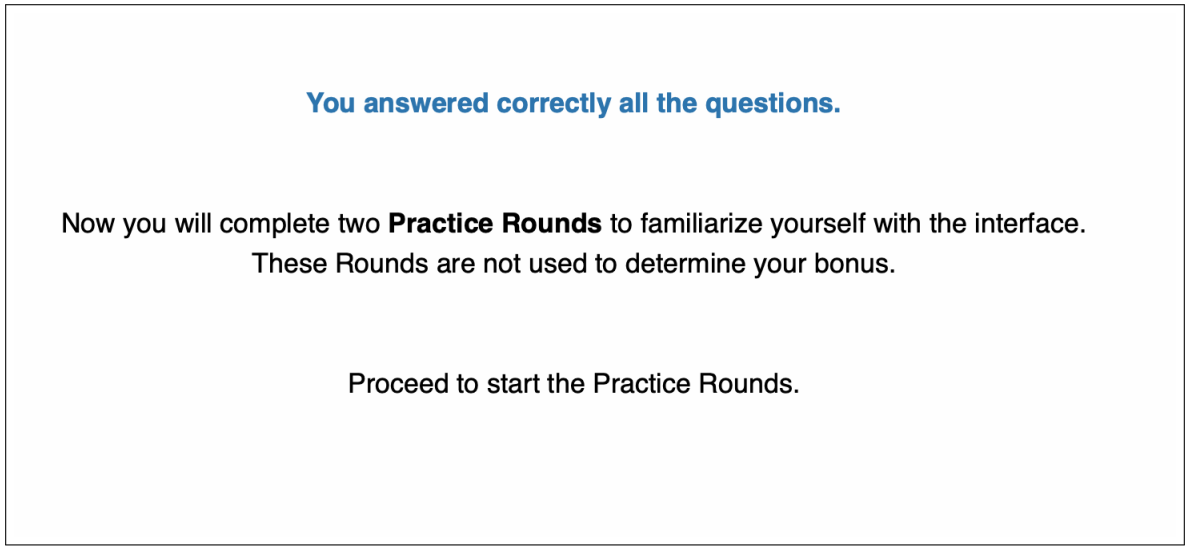


Figure 9: Message before practice rounds

Link to Instructions

Your color is Orange

Chances to get a score between	when your color is Orange
88 and 100	2%
75 and 87	5%
63 and 74	8%
50 and 62	11%
38 and 49	14%
25 and 37	18%
13 and 24	20%
0 and 12	23%

Chances to get a score between	when your color is Blue
88 and 100	23%
75 and 87	21%
63 and 74	17%
50 and 62	15%
38 and 49	11%
25 and 37	8%
13 and 24	5%
0 and 12	2%

Click on the schools' names (A, B, C, ...) in the table below to make your selection.
The first school you select it your 1st choice, the 2nd school you select is your 2nd choice, etc.

When you select a school it will show up in your choice list (the table on the right).

You can start over by clicking on the "Clear" button.

You need to select at least one school.

Click on "submit" at the bottom of the page when you're ready (the button will show up as soon as you have selected one school).

Figure 10: Practice round

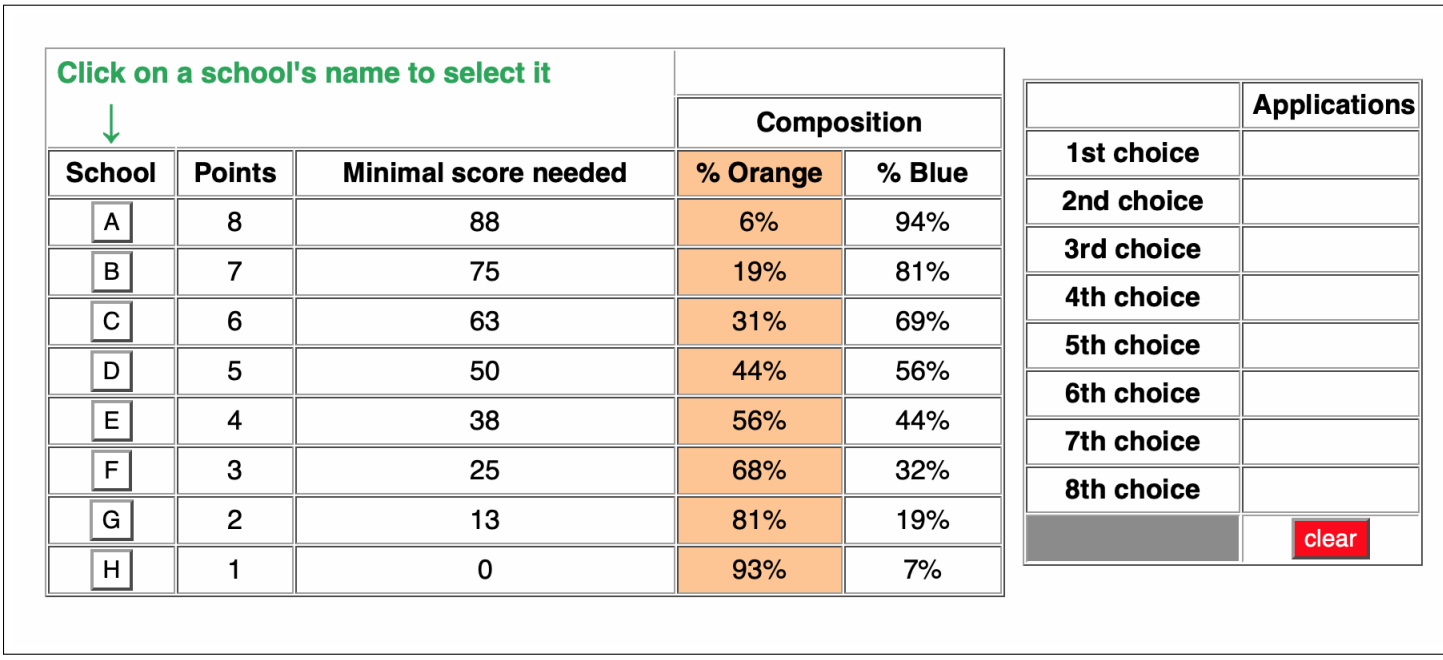


Figure 11: Practice round

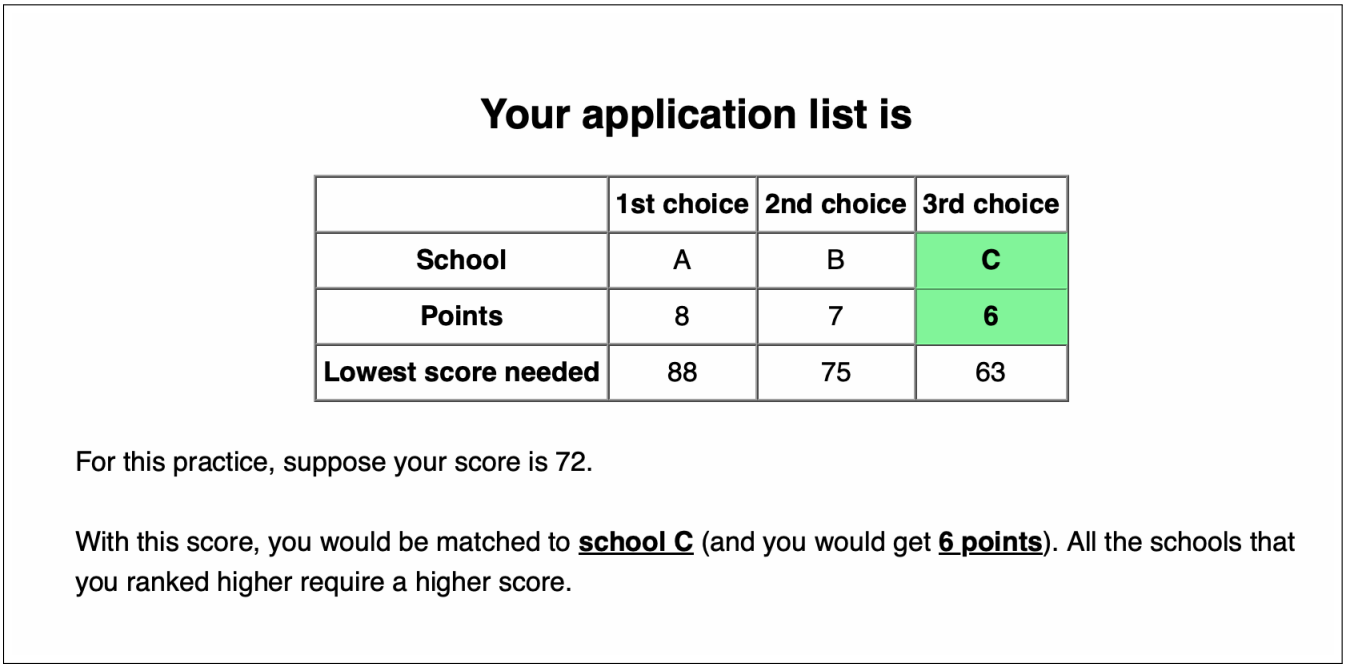


Figure 12: Feedback from practice round

Your application list is

	1st choice	2nd choice	3rd choice	4th choice	5th choice	6th choice	7th choice	8th choice
School	A	B	C					
Points	8	7	6					
Lowest score needed	88	75	63					

For this practice, suppose your score is 17.

With this score, you are not matched to any school (you get 0 point): All the schools you put in your choice list require a higher score than 17.

Figure 13: Feedback from practice round (if not assigned to any school)

You completed the Practice Round.
You can now start the main task.

You will complete 18 Rounds.
One of them will be randomly selected to determine your bonus.

Important: in the practice rounds you got to know your score (and thus the school you got).

For the next 18 rounds, you will not know your score.

Figure 14: Message before main rounds

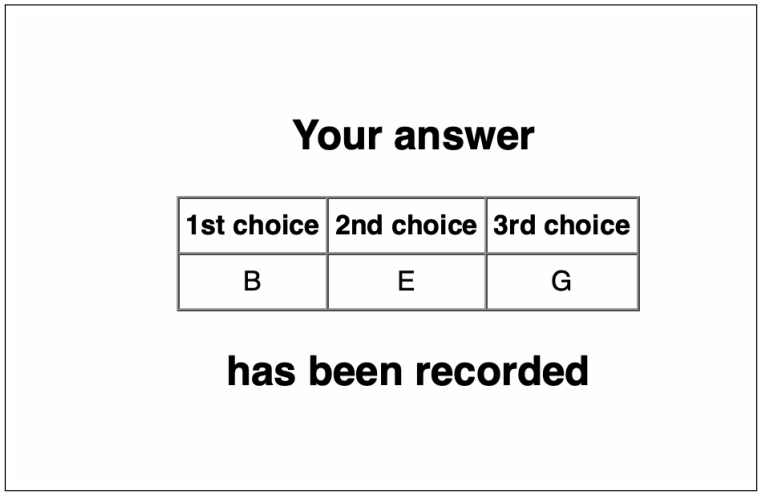


Figure 15: Feedback after submitted choices (for the 18 regular rounds)

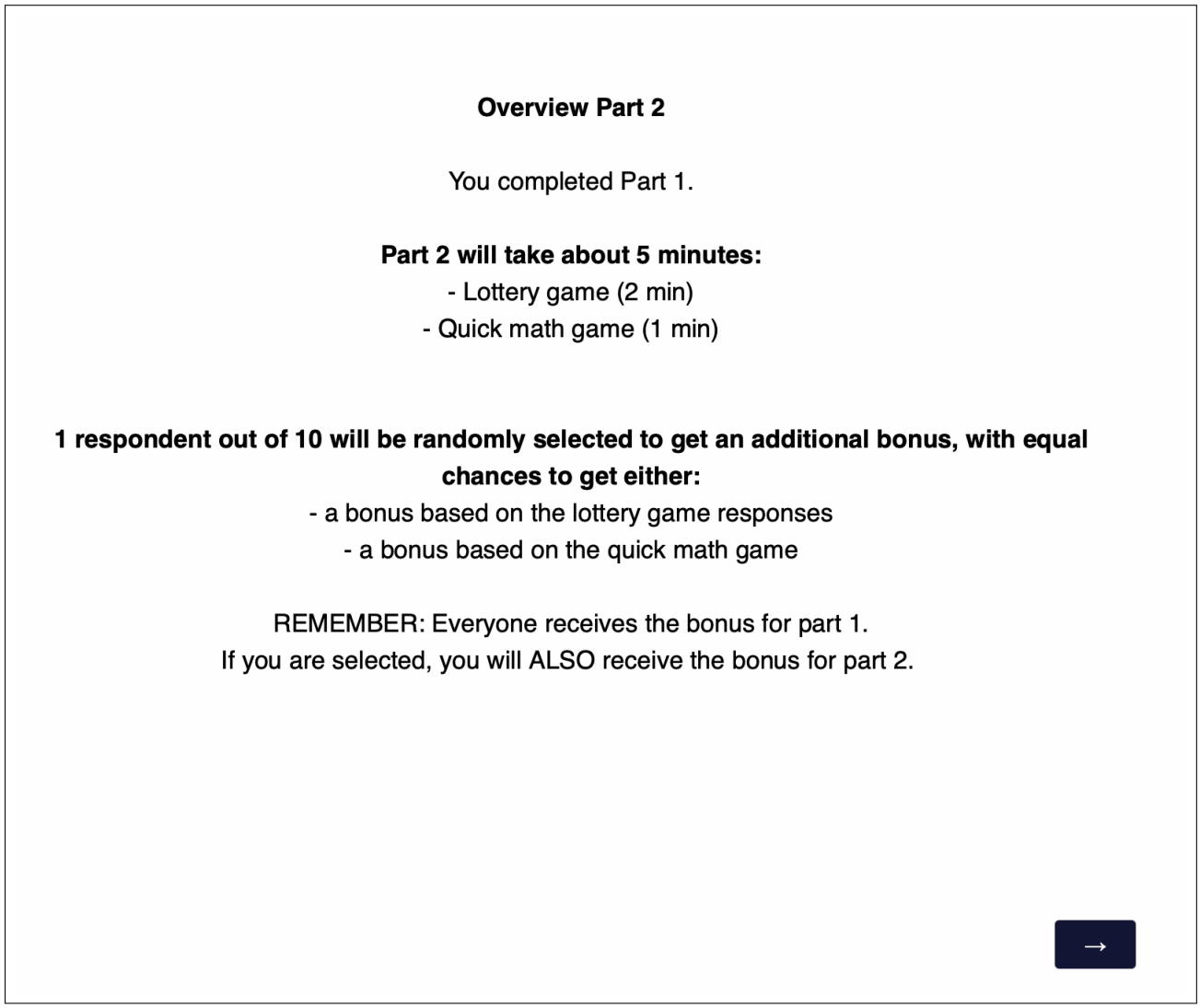


Figure 16: Message before 2nd part of experiment (after 18 rounds)

Lottery Game

On the next page, you will be presented with 10 "lotteries".
For each of them, indicate how much YOU value that lottery.

The lotteries will look for instance like this:
50% chance of $ 4
50% chance of $ 1
This means that there are two possible prizes: either $4 or $1.
You have a 50% (one-half) chance of each of them (either $4 or $1).

Figure 17: Lottery game (Instructions — part 1)

Lottery Game

On the next page, you will be presented with 10 "lotteries".
For each of them, indicate how much YOU value that lottery.

The lotteries will look like this:
50% chance of $ 4
50% chance of $ 1
This means that there are two possible prizes: either $4 or $1.
You have a 50% (one-half) chance of each of them (either $4 or $1).

If you are selected for the extra bonus,
one of your choices will determine the bonus.
You can read the details below.

How is the bonus determined?
A "price" for the lottery will be drawn randomly between $0 and $8 (in increments of 1 cent).
Any possible price has an equal chance of being selected.
If the random price is higher than your evaluation, then you receive the random price.
If the random price is lower than (or equal to) your evaluation, then you receive the lottery (and a random draw will determine how much you get).

Figure 18: Lottery game (Instructions — part 2)

Figure 19: Lottery game

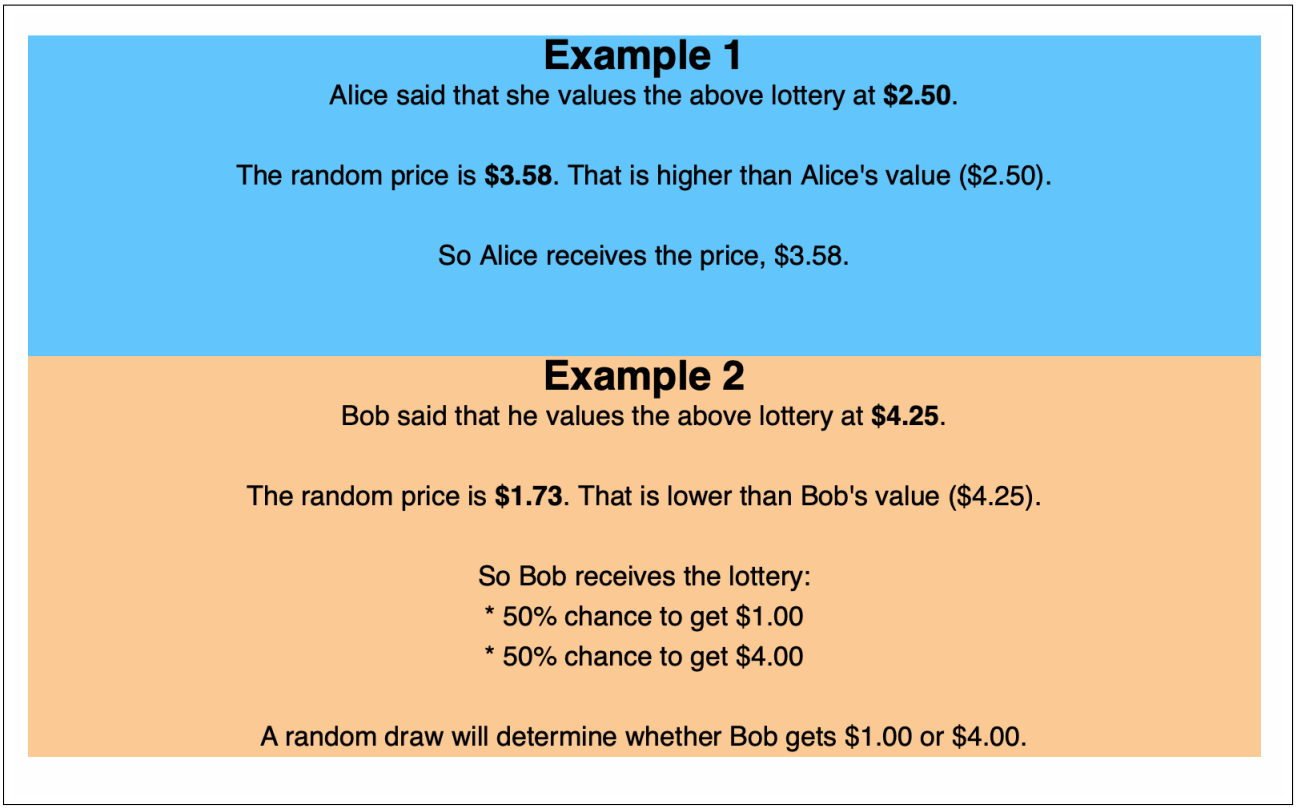


Figure 20: Lottery game (Instructions — part 3)

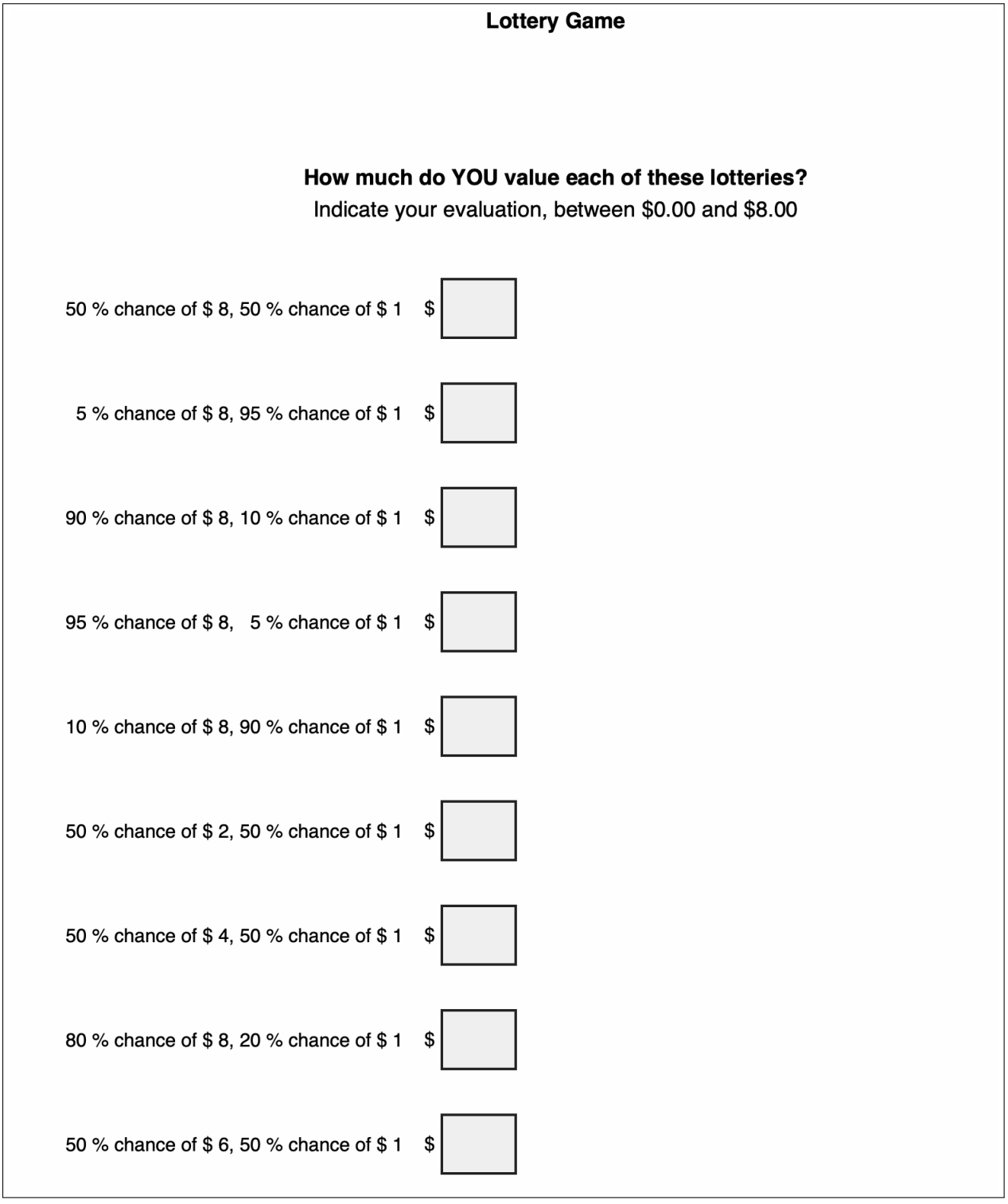


Figure 21: Lottery game (form for choices)

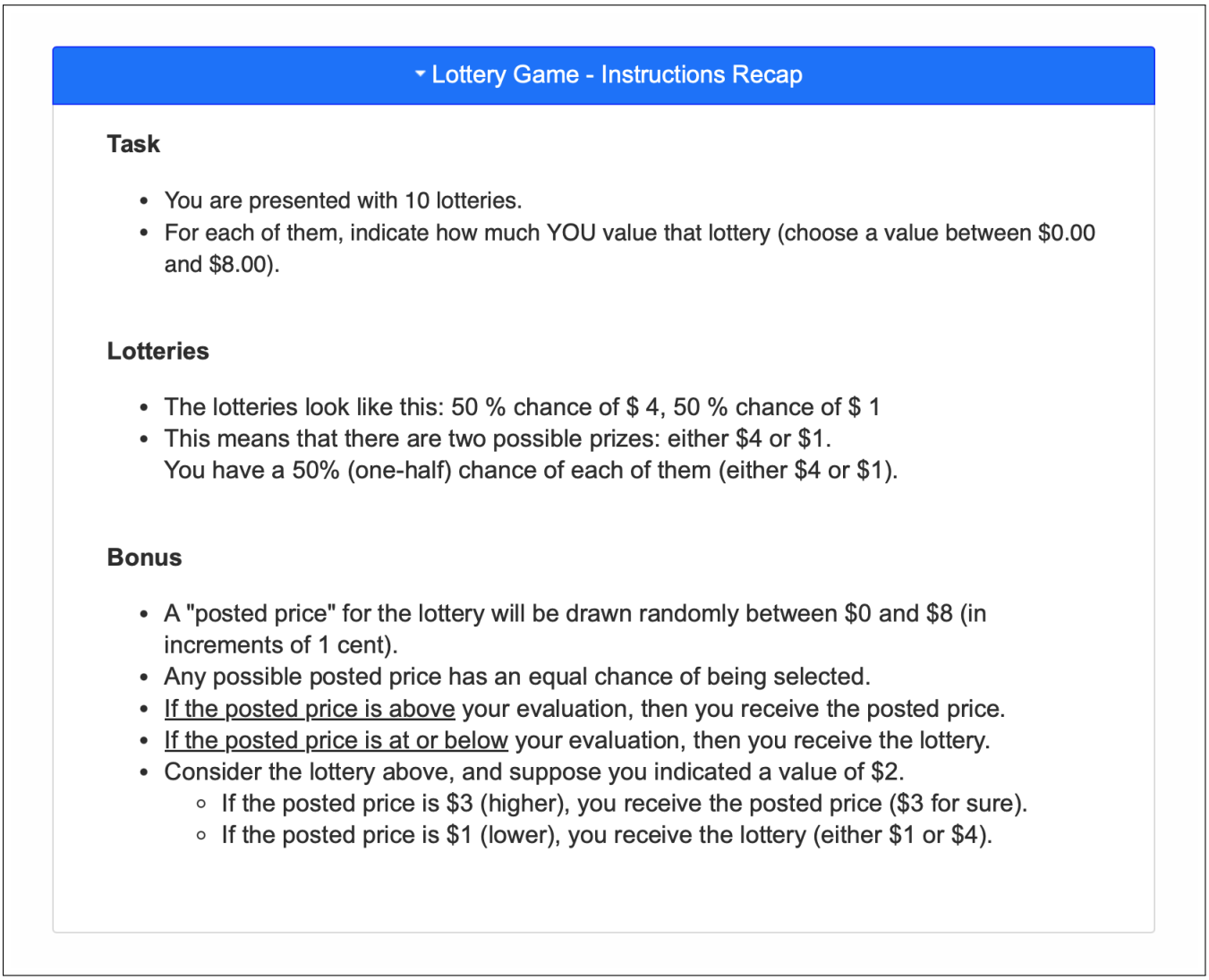


Figure 22: Lottery game (Instructions reminder (on the same page as form for choices)

Quick Math Game

On the next page, you will be presented with a series of quick math questions.
You have 30 seconds.

Try to complete as many questions as possible.

The questions will look like this:
6 + 5 - 1 + 9 = ...
1 + 8 - 9 + 6 = ...

(In these examples, the correct answers are 19 and 6)

How is the bonus determined?
If you are selected for the extra bonus,
you will get $1 for each correct answer.

You can use the TAB key to move quickly to the next question.
Press the arrow to start.

Figure 23: Math quiz (Instructions)

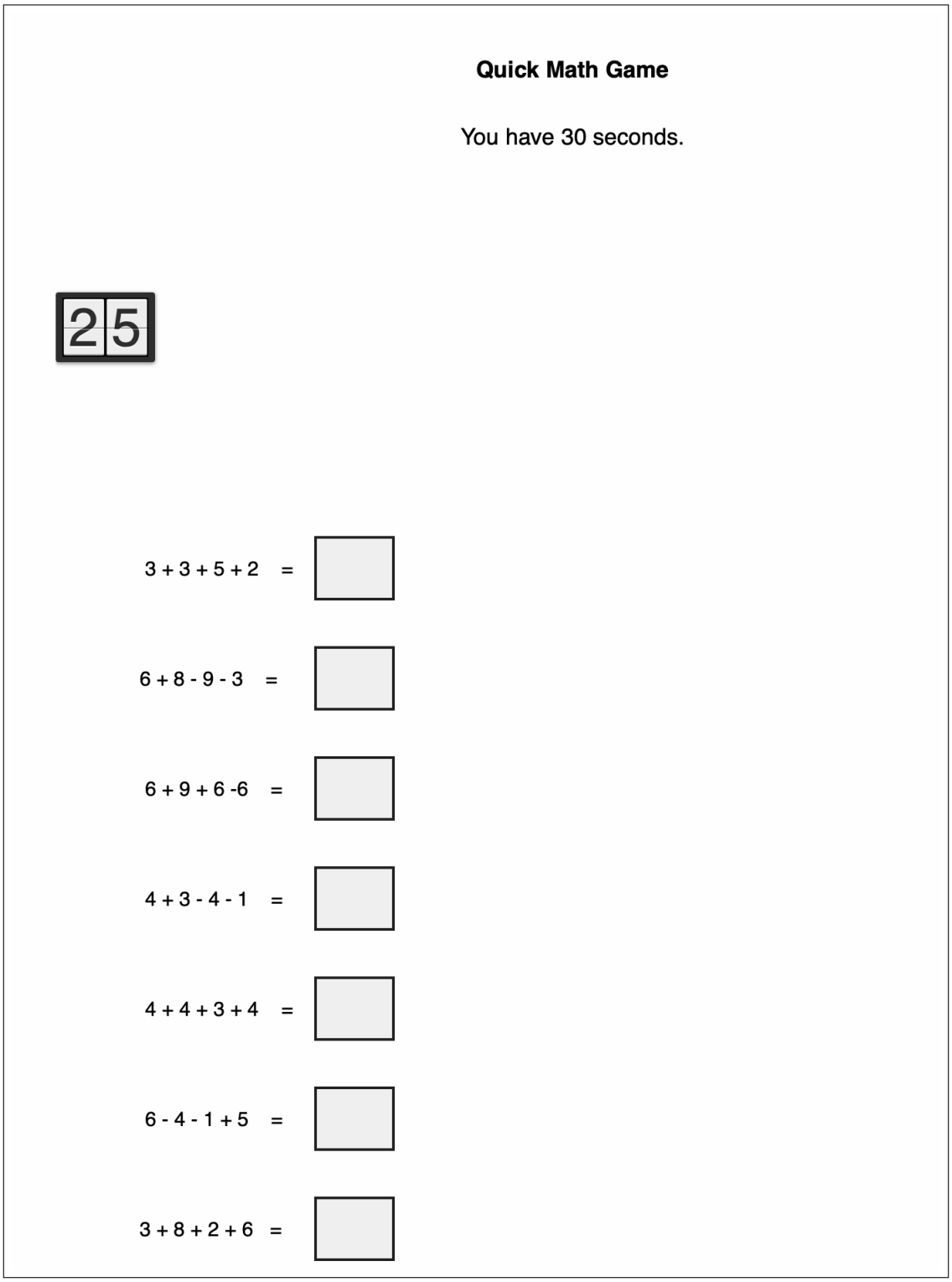


Figure 24: Math quiz (form)

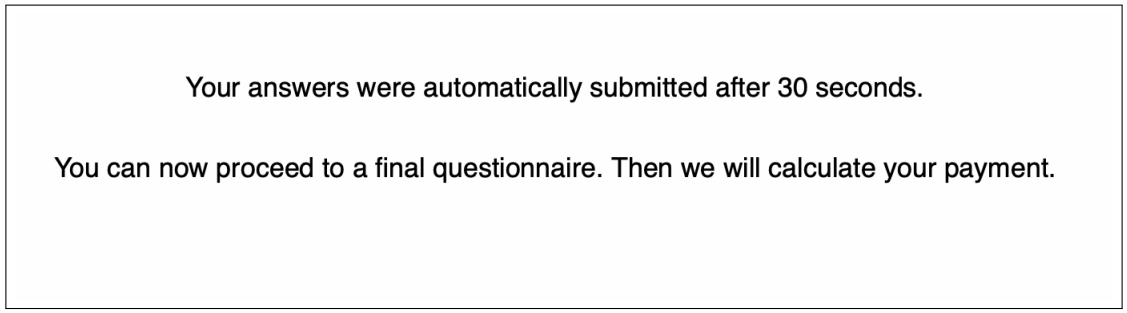


Figure 25: Math quiz (end message)

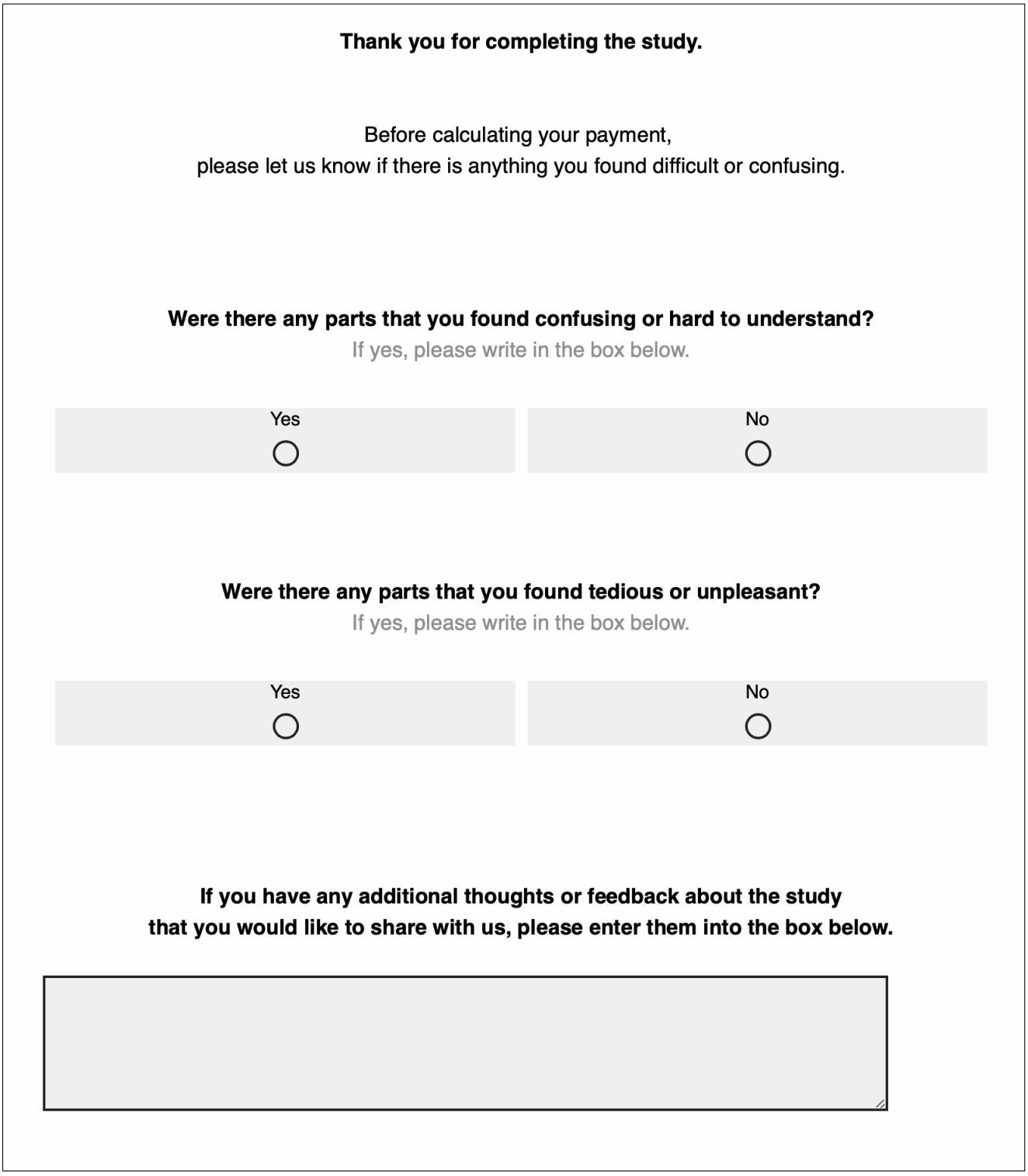


Figure 26: Feedback form

We will now calculate your payment

In the next page:

- A round will be randomly chosen
- A score will be randomly chosen
  Remember: blue students are likely to have a high score, and orange students are likely to have a low score.
- The school you will get will be determined by your choices for that round, your score, and the minimal score needed for each school.
- You will be selected at random to get a bonus from either the lottery task or the math task.
  Remember that there is:
  - 5% chance to be selected for the lottery task
  - 5% chance to be selected for the math task
    (You cannot be selected for both the lottery and the math tasks.)

We will then calculate your total payment.

Figure 27: Payment announcement

Period 7 has been randomly selected
In that period your color was "Blue" and your score is 23.

Your choices for that period are given in the table below

	1st choice	2nd choice	3rd choice
School	C	E	
Points	C	4	
Lowest score needed	63	38	

With this score, you are not matched to any school: All the schools in your list require a higher score than 23. You get 0 point.

You have not been selected
for the lottery or the math bonus.

Your total earnings are

Concept	Amount
Participation fee	$4.00
School assignment	$0.00
Total	**$4.00**

You will receive from Prolific £3.24.

Figure 28: Payment calculation (if not selected for extra bonus)

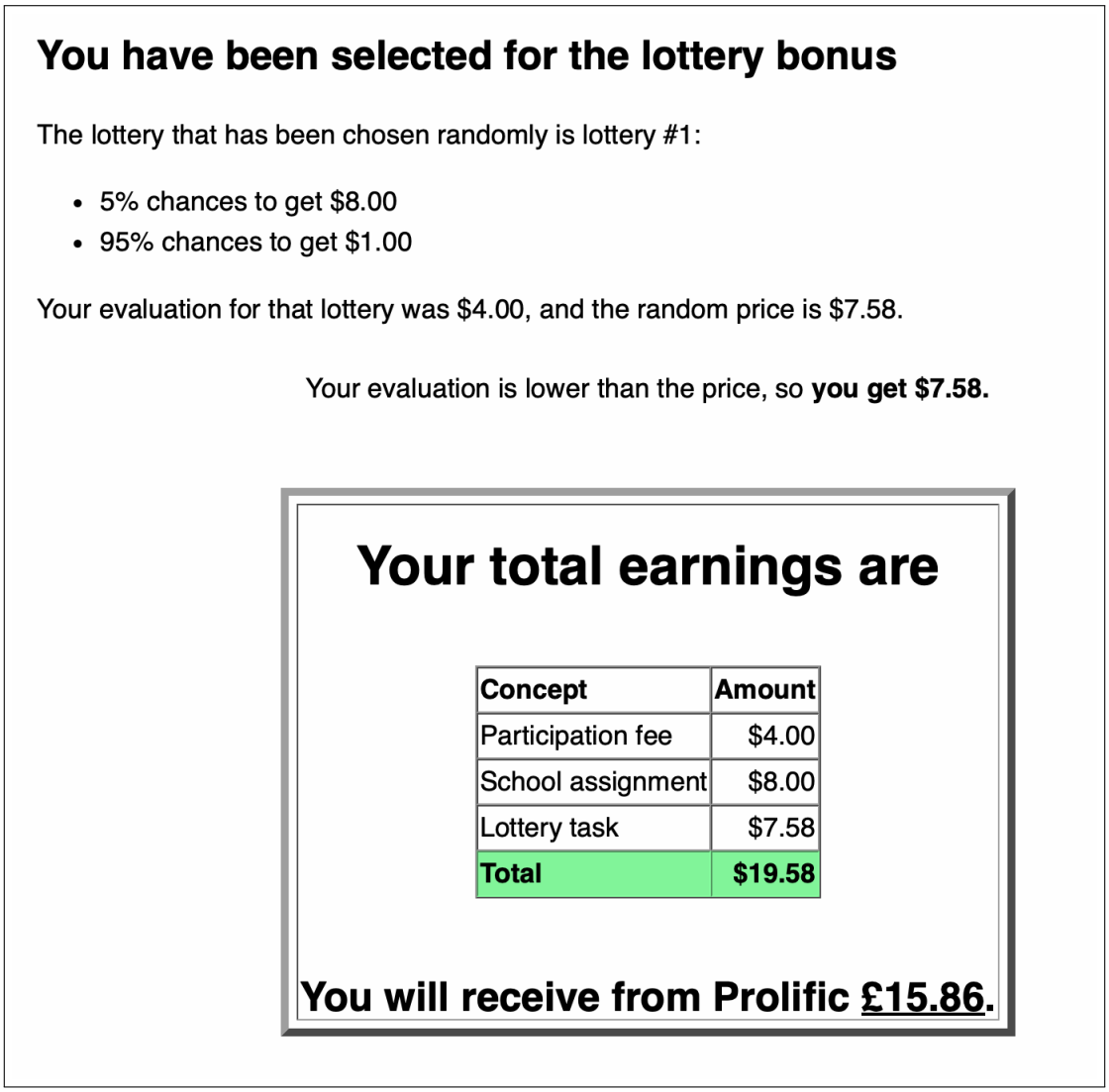


Figure 29: Payment calculation (if selected for lottery bonus)

You have been selected for the math bonus.

Question	Correct answer	Your answer	Points
3 + 9 - 3 + 7 =	16	16	1
3 + 8 + 2 + 6 =	19	15	0
6 + 8 - 9 - 3 =	2	2	1
6 + 4 + 2 + 5 =	17	17	1
6 + 9 + 6 - 6 =	15	19	0

Question	Correct answer	Your answer	Points
6 - 4 - 1 + 5 =	6	6	1
3 + 3 + 5 + 2 =	13	15	0
4 + 3 - 4 - 1 =	2	2	1
4 + 4 + 3 + 4 =	15	NaN	0
4 + 5 + 2 - 6 =	5	NaN	0

You earned 5 points for this task.

Your total earnings are

Concept	Amount
Participation fee	$4.00
School assignment	$0.00
Math task	$5.00
Total	**$9.00**

You will receive from Prolific £7.29.

Figure 30: Payment calculation (if selected for math quiz bonus)

To validate your participation to this survey, click here: **www.prolific.com**.

Clicking on the above link will complete your participation (the completion code is included in the link). In case there is an issue, the completion code is **C10M93XZ. We will review your payment and bonus in the next few days.**

Thank you for your participation.

Figure 31: Post payment message

Figure 32: Choice screen for Control, blue student, unconstrained, tight cutoffs

Figure 33: Choice screen for Control, orange student, constrained, tight cutoffs

Figure 34: Choice screen for Control, orange student, unconstrained, loose cutoffs

Your color is Blue

Chances to get a score between	when your color is Orange
88 and 100	2%
75 and 87	5%
63 and 74	8%
50 and 62	11%
38 and 49	14%
25 and 37	18%
13 and 24	20%
0 and 12	23%

Chances to get a score between	when your color is Blue
88 and 100	23%
75 and 87	21%
63 and 74	17%
50 and 62	15%
38 and 49	11%
25 and 37	8%
13 and 24	5%
0 and 12	2%

School	Points	Minimal score needed	Chances of admission: % Orange	Chances of admission: % Blue
A	8	88	2%	22%
B	7	75	6%	44%
C	6	63	14%	60%
D	5	50	25%	75%
E	4	38	39%	85%
F	3	25	56%	94%
G	2	13	76%	98%
H	1	0	100%	100%

Applications

1st choice

2nd choice

3rd choice

clear

Figure 35: Choice screen for Probability, blue student, constrained, balanced cutoffs

Your color is Orange

Chances to get a score between	when your color is Orange
75 and 100	7%
53 and 74	16%
38 and 52	17%
26 and 37	16%
17 and 25	14%
10 and 16	12%
4 and 9	11%
0 and 3	7%

Chances to get a score between	when your color is Blue
75 and 100	46%
53 and 74	28%
38 and 52	14%
26 and 37	8%
17 and 25	4%
10 and 16	2%
4 and 9	1%
0 and 3	Less than 1%

School	Points	Minimal score needed	Chances of admission: % Orange	Chances of admission: % Blue
A	8	75	6%	44%
B	7	53	22%	72%
C	6	38	39%	85%
D	5	26	55%	93%
E	4	17	69%	97%
F	3	10	81%	99%
G	2	4	92%	100%
H	1	0	100%	100%

Applications

1st choice

2nd choice

3rd choice

clear

Figure 36: Choice screen for Probability, orange student, constrained, loose cutoffs

Round 4 out of 18

Link to Instructions

Your color is Orange

Chances to get a score between	when your color is Orange
75 and 100	7%
53 and 74	16%
38 and 52	17%
26 and 37	16%
17 and 25	14%
10 and 16	12%
4 and 9	11%
0 and 3	7%

Chances to get a score between	when your color is Blue
75 and 100	46%
53 and 74	28%
38 and 52	14%
26 and 37	8%
17 and 25	4%
10 and 16	2%
4 and 9	1%
0 and 3	Less than 1%

			Chances of admission	
School	Points	Minimal score needed	% Orange	% Blue
A	8	75	6%	44%
B	7	53	22%	72%
C	6	38	39%	85%
D	5	26	55%	93%
E	4	17	69%	97%
F	3	10	81%	99%
G	2	4	92%	100%
H	1	0	100%	100%

	Applications
1st choice	
2nd choice	
3rd choice	
4th choice	
5th choice	
6th choice	
7th choice	
8th choice	
	clear

Figure 37: Choice screen for Probability, orange student, unconstrained, loose cutoffs

Figure 38: Choice screen for Composition, blue student, constrained, balanced cutoffs

Figure 39: Choice screen for Composition, blue student, constrained, tight cutoffs

Round 2 out of 18

Link to Instructions

Your color is Orange

Chances to get a score between	when your color is Orange
96 and 100	Less than 1%
90 and 95	1%
83 and 89	2%
74 and 82	4%
62 and 73	8%
47 and 61	14%
25 and 46	28%
0 and 24	43%

Chances to get a score between	when your color is Blue
96 and 100	10%
90 and 95	11%
83 and 89	12%
74 and 82	14%
62 and 73	16%
47 and 61	16%
25 and 46	16%
0 and 24	6%

	School	Points	Minimal score needed	Composition % Orange	Composition % Blue
	A	8	96	1%	99%
	B	7	90	5%	95%
	C	6	83	6%	94%
	D	5	74	13%	87%
	E	4	62	19%	81%
	F	3	47	38%	62%
	G	2	25	61%	39%
	H	1	0	89%	11%

	Applications
1st choice	
2nd choice	
3rd choice	
4th choice	
5th choice	
6th choice	
7th choice	
8th choice	

clear

Figure 40: Choice screen for Composition, orange student, unconstrained, tight cutoffs

Figure 41: Choice screen for Composition 2, blue student, constrained, balanced cutoffs

Your color is Blue

Chances to get a score between	when your color is Blue
88 and 100	23%
75 and 87	21%
63 and 74	17%
50 and 62	15%
38 and 49	11%
25 and 37	8%
13 and 24	5%
0 and 12	2%

Chances to get a score between	when your color is Orange
88 and 100	2%
75 and 87	5%
63 and 74	8%
50 and 62	11%
38 and 49	14%
25 and 37	18%
13 and 24	20%
0 and 12	23%

	Composition				Applications
	School	Points	Minimal score needed	% Orange	% Blue	
	A	8	88	4%	96%	1st choice
	B	7	75	12%	88%	2nd choice
	C	6	63	8%	92%	3rd choice
	D	5	50	30%	70%	4th choice
	E	4	38	49%	51%	5th choice
	F	3	25	58%	42%	6th choice
	G	2	13	75%	25%	7th choice
	H	1	0	94%	6%	8th choice
						clear

Figure 42: Choice screen for Composition 2, blue student, unconstrained, balanced cutoffs

Figure 43: Choice screen for Composition 2, orange student, constrained, loose cutoffs