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Aiding Applicants: Leveling the Playing Field within the Immediate Acceptance Mechanism

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Abstract

In school choice problems, the widely used manipulable Immediate Acceptance mechanism (IA) disadvantages unsophisticated applicants, but may ex-ante Pareto dominate any strategy-proof alternative. In these cases, it may be preferable to aid applicants *within* IA, rather than to abandon it. In a laboratory experiment, we first document a substantial gap in strategy choices and outcomes between subjects of higher and lower cognitive ability under IA. We then test whether disclosing information on past applications levels the playing field. The treatment is effective in partially reducing the gap between applicants of above- and below-median cognitive ability and in curbing ability segregation across schools, but may leave the least able applicants further behind.

Keywords: laboratory experiment, school choice, immediate acceptance, strategy-proofness, cognitive ability, mechanism design.

JEL codes: C78, C91, D82, I24.

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1 Introduction

A desire for equity is among the central motivations behind many school choice programs, which extend access to good schools to otherwise ineligible students. Equity may however be compromised where students have to apply through a mechanism that is not strategy-proof so that optimal application strategies are hard to identify. Better-informed and strategically sophisticated applicants may then be at an advantage.

The argument that less sophisticated applicants are disadvantaged under the widely used but manipulable Immediate Acceptance mechanism (henceforth IA, also known as Boston Mechanism) has been at the core of many recent reforms that replaced it with strategy-proof mechanisms, in particular the deferred acceptance mechanism. For example, in 2005 Boston abandoned its old immediate acceptance mechanism after observing that "the need to strategize provides an advantage to families who have the time, resources and knowledge to conduct the necessary research" [Pathak and Sönmez, 2008].[1]

On the other hand, under the realistic assumption that applicants' preferences are correlated and schools' priorities are coarse, immediate acceptance may *in equilibrium* improve upon deferred acceptance according to various ex-ante efficiency and welfare criteria [Abdulkadiroğlu et al., 2011; Miralles, 2009; Troyan, 2012].[2] Hence, when this is likely to be the case, it would seem preferable not to abandon IA, but to protect unsophisticated applicants *within* the mechanism by making it easier for them to identify optimal strategies.[3]

Intuitively, IA is able to generate welfare gains as advantageous misrepresentation of ordinal preferences reveals information on preference intensities[4]—only students with a sufficiently high valuation would be willing to apply at highly oversubscribed schools, while students for which a less popular school is almost as good would instead apply at the latter. To help applicants identify schools that are likely to be oversubscribed, a school council might decide to disclose information on the number of applicants at various schools in previous years. Assuming that the distribution of applicants' preferences over the years is sufficiently stable, these figures should be informative of the expected number of applicants in the current year and hence help applicants to identify optimal strategies and settle on an equilibrium. If successful this renders everyone a best responder, thus eliminating the gap between formerly 'sophisticated' and 'unsophisticated' applicants, and in addition allows to reap the improvements in ex-ante welfare that IA can in theory provide.

In [Basteck and Mantovani, 2018] we report experimental evidence confirming that—absent detailed information on previous applications—IA creates a gap between subjects of different cognitive ability. Subjects of higher ability fare better than their peers of lower ability: because they are less able to

[1] Similarly concerned over its strategic complexity, England banned the use of *first preference first* mechanisms such as IA in 2007 and many local authorities moved to deferred acceptance. For an overview of recent reforms, in England and beyond see Coldron et al. [2008]; Pathak and Sönmez [2013].

[2] IA may also Pareto-dominate the outcome under deferred acceptance at some equilibrium when priorities are strict but preferences are submitted sequentially [Dur et al., 2017]; the converse holds when preferences are submitted simultaneously and priorities are strict [Ergin and Sönmez, 2006].

[3] In addition, deferred acceptance may create incentives for schools to manipulate by concealing capacity – which can be ruled out under IA [Kesten, 2012].

[4] See also Abdulkadiroğlu et al. [2015] who propose a modified deferred acceptance mechanism designed to reveal cardinal information.

identify optimal strategies in IA, the latter earn significantly less and are over-represented at the worst school, resulting in ability segregation across schools.[5] Nevertheless, IA is able to generate significant welfare improvements over deferred acceptance, both in equilibrium and in the data, as sufficiently many subjects are able to identify optimal strategies.

Here we test experimentally whether providing information on previous applications can increase the welfare of subjects of lower cognitive ability within IA, reduce the gap between subjects of higher and lower ability and help to avoid ability segregation across schools.[6]

Since the failure to anticipate others' application behavior is one likely source of strategic mistakes, enhanced information may benefit subjects of low ability. Yet information on others' strategies needs to be complemented with an understanding of their consequences for acceptance probabilities at schools. Since subjects of higher cognitive ability may be better able to make use of the provided information, information provision may end up widening the gap between low and high ability subjects and could further disadvantage the former.

In our experiment, we first measure participants' cognitive ability by means of a Raven test before letting them play several school choice games under IA. For the information treatment, participants are informed of the number of applicants that listed each school first in a previous game where the distribution of preferences was identical. We compare their choices and outcomes to those obtained in a control treatment where information about past strategies is not provided.

We use two preference profiles designed to bring out two intuitive strategic manipulations – in the words of the West Zone Parents Group:[7]

> One school choice strategy is to find a school you like that is undersubscribed and put it as a top choice, OR, find a school that you like that is popular and put it as a first choice and find a school that is less popular for a "safe" second choice.

In equilibrium under our first preference profile, applicants predominantly choose the latter manipulation (*Skip-the-Middle*), as their second-most preferred school will be oversubscribed and ranking it second would loose them the chance to be admitted in the second round. In our second preference profile, a majority of students should instead choose the former manipulation (*Skip-the-Top*), as their most preferred school is heavily oversubscribed in equilibrium. In both cases, knowing the demands of the past period may allow students to form a more precise prediction and use a more appropriate strategy in the current period.

We find that on aggregate, subjects choose optimal strategies significantly more often when information is provided. While subjects of high cognitive ability are more likely to choose a best reply than

[5] We show subjects of low ability are not simply more sincere, but also make more use of suboptimal manipulations. This is relevant because in models with only naive and sophisticated players and coarse priorities, it is not always the case that the latter fare better than the former [Babaioff et al., 2019]. In this sense, we identify a disadvantage that is more general – i.e., not specific to the environment – than mechanical naïveté .

[6] Calsamiglia et al. [2017] show how segregation by ability may emerge *in equilibrium* if higher types care more about their peers' ability than lower types. In contrast, we study ability segregation that arises out of applicants' (different propensities for) strategic mistakes.

[7] Meeting minutes, October 27, 2003, see [Pathak and Sönmez, 2008]. The group connects parents to share information on how to choose and register for a school in the Boston Public School system.

their low ability peers in the absence of information, this gap between the two groups is reduced significantly in the information treatment. Moreover, as a result, ability segregation is significantly lower in the information treatment for both preference environments. Despite this, subjects of lower cognitive ability earn significantly less than their peers both with and without information and the gap in payoffs does not decrease significantly. The evidence suggests the persistence of this gap, though partly specific to the payoffs used in the experiment, is connected to a qualitative difference in the use of the additional information by subjects of different ability. Perhaps more worryingly, in one preference environment information leaves subjects in the lower tail of the distribution of cognitive abilities further behind, so that the gap in payoffs between the top and bottom 20 percent increases with information.

Other school choice experiments have varied the information provided to subjects. Pais and Pintér [2008] vary information about others' preferences exogenously and find that truthtelling in IA increases as applicants have less information available.[8] Chen and He [2021] show that providing information on others' preferences, and hence indirectly on admission chances, reduces wasteful investment in information acquisition under IA. Providing historical cutoff scores can likewise increase welfare where information costs are high [Hakimov et al., 2021]. Another way to provide information on admission chances used in practice, consists in publishing the current number of applications at different schools allowing students to revise their own applications over the course of the application period. Such data may be provided at the discretion of individual schools as, for example, in Amsterdam [De Haan et al., 2015] or Berlin [Basteck et al., 2015] or systematically, e.g., by the Wake County Public School System in North Carolina [Dur et al., 2018]. Here, using field data, Dur et al. [2018] are able to classify students as 'sincere' or 'sophisticated' based on whether they access this information repeatedly over the course of the application period and show that, under IA, sophisticated students tend to avoid over-demanded schools and are hence more likely to receive an assignment.

A potential downside of making other players' strategies observable is reported by Guillen and Hakimov [2017] who show that revealing the use of sub-optimal strategies by opponents may lead subjects to choose dominated strategies more often. In contrast, Guillen and Hakimov [2018] demonstrate for the same mechanism that direct advice on optimal strategies can increase their use.[9]

Our interest in IA is motivated in particular by its potential welfare improvements over deferred acceptance, which relates our work to papers that perform a welfare comparison between the two. Featherstone and Niederle [2016] consider an incomplete information environment where truth-telling is an equilibrium under IA and find a majority of subjects to report truthfully. As a result IA's natural advantage in satisfying stated preferences also yields higher welfare with respect to true preferences. In contrast, Chen and Sönmez [2006] find deferred acceptance to yield higher average expected payoffs in a designed preference profile and no difference in a random profile. In Chen and Kesten [2019] welfare under IA may be higher or lower than under deferred acceptance, depending on the environment.[10]

[8] See also Pais et al. [2011] in the context of college admissions.

[9] Two other experiments that focus on the effect of advice in a school choice context are [Ding and Schotter, 2017], where the advice is shared by peers in a network, and [Ding and Schotter, 2019], where it is shared intergenerationally. We refer to the recent surveys in Pan [2020] and Hakimov and Kübler [2021] for a thorough coverage of experiments in school choice.

[10] By construction the designed profile of Chen and Sönmez [2006] and both environments in Chen and Kesten [2019] shut off an important channel by which IA may yield an improvement over deferred acceptance, as there are no variations in preference intensities that may be revealed by strategic manipulation.

Basteck and Mantovani [2018] compare IA and deferred acceptance using the same preference profiles as in this paper. Here, manipulations under IA should in theory reveal additional information and improve welfare. The effect is borne out in the results. Finally, recent field work using data from Barcelona [Calsamiglia et al., 2020] and Beijing [He, 2015] also speaks in favor of IA in terms of aggregate welfare. Both papers estimate applicants' preferences given observed applications under IA and compare it to the deferred acceptance outcome under the assumption of truthtelling. In contrast, De Haan et al. [2015] find deferred acceptance to yield higher aggregate welfare, using application data from Amsterdam where IA is used. Eliciting preferences in a survey, they compute the counterfactual outcome under deferred acceptance under the assumption of truthtelling. However, their survey also documents that many applicants hold incorrect beliefs regarding the availability of schools; for example many respondents consider schools to be oversubscribed that are in fact undersubsribed and where consistently undersubscribed in recent years. Kapor et al. [2020] also report evidence that applicants beliefs about others' strategies are often incorrect, and show this causes welfare losses. Hence, their findings also suggest that information provision on past applications should increase welfare under IA.

The paper is organized as follows. Section 2 introduces the school choice environments, experimental design and procedures. Section 3 describes our hypotheses. Results follow in Section 4. Section 5 concludes.

2 Experiment

2.1 School choice game – matching mechanism and equilibria

Our setup features 4 schools $s \in S = \{A, B, C, D\}$, with 4 seats each. Competing for these seats are 16 students, 4 of each (preference) type. Each student i admitted to a school s receives a payoff $p(s, t_i)$ that depends on both the school s and her own type $t_i \in T = \{1, 2, 3, 4\}$.

Students report a ranking of schools $\succ_i$, i.e. a strict linear order on S, that determines the order in which they apply to different schools. To break ties among applicants in the case of over-subscription, a uniform lottery assigns to each student a different number between 1 and 16. The Immediate Acceptance mechanism (IA) then generates a matching between students and schools as follows.

> ROUND 1. Each student applies at the school that she ranked first. If there are at most 4 students applying at a school, they are admitted. If there are more than 4 students applying, the school admits the 4 applicants with the lowest lottery number.
>
> ROUND $k > 1$. Each student who has not yet been admitted, applies at the school that she ranked at the k^{th} position. The school admits applicants in the order of their lottery numbers until either it has admitted 4 students in total (including previous rounds) or there are no more applicants who have ranked the school in k^{th} position.
>
> With as many seats as students, each student is admitted to some school when the algorithm terminates after at most 4 rounds.

We study two different preference profiles, henceforth P1 and P2. Payoffs are given in Table 1. Both

TABLE 1: PAYOFFS IN P1 (LEFT PANEL) AND P2 (RIGHT PANEL)

$p(s, t_i)$	School A	School B	School C	School D	School A	School B	School C	School D
Type 1	20	10	6	0	20	11	7	0
Type 2	16	17	6	0	16	15	7	0
Type 3	16	10	8	0	16	11	11	0
Type 4	16	10	6	0	16	11	7	0

Notes: each cell represents the payoff a student of type t_i obtains when admitted at school s in the relevant preference profile.

profiles are designed to capture a situation where applicants' preferences are correlated but not perfectly aligned. School D is universally considered the worst school with an associated payoff of zero. Students of type 1, 2 and 3 earn a higher payoff than others at school A, B, and C, respectively. This creates heterogeneity in preference intensities and in some cases also in the ordinal ranking of schools.

The associated pure-strategy equilibria are as follows: [11]

Equilibria in P1.

In every pure strategy Nash equilibrium of the game induced by IA-P1 :

- *11 students report* $A \succ_i C \succ_i B, D$*: all type* 1 *and 7 out of the 8 type* 3 *and* 4
- *5 students reports* $B \succ_i C \succ_i A, D$*: all type* 2 *and 1 out of the 8 type* 3 *and* 4

Equilibria in P2.

In every pure strategy Nash equilibrium of the game induced by IA-P2 :

- *all students of type* 1 *and three of type* 4 *report* $A \succ_i C, B, D$
- *all students of type* 2 *and one of type* 4 *report* $B \succ_i C, A, D$
- *all students of type* 3 *report* $C \succ_i A, B, D$
- *some students of type* 1*,* 2*, and* 4 *rank* C *second.*

The intuition for the equilibrium in P1 is as follows. Both A and B are most-preferred by at least 4 students and hence will be filled in the first round. Since the payoff from C is relatively low even for type 3 students, no one will initially apply at C. Since in the second round, only schools C and D have available seats, all initially rejected students should apply at C in the second round. Weighing a higher payoff from A against a lower admission probability, one additional student besides the four students of type 2 will initially apply at B in order to avoid the heavily over-subscribed school A. This student will be either of type 3 or 4, as students of type 1 receive a higher payoff at school A.

For the equilibrium in P2 where A is everyone's most-preferred school, we find that types 2 and 3 find B and C sufficiently valuable such as to initially apply there and avoid the heavily over-subscribed school A. Students of type 4 will split between applying at A and B, again weighing a higher payoff from A against a higher admission probability at B. Finally, while all three schools A, B, and C are filled in the first round, we verify that in equilibrium some students rank C second – otherwise, type 3 would

[11] Calculations can be found in Basteck and Mantovani [2018]. The equilibria are computed under the assumption of risk neutrality.

initially apply to A, trusting that they could still be admitted to C in the second round. That however would make everyone else rank C second which in turn would lead type 3 to initially apply at C.

2.2 Experimental design

In each session, subjects face three different tasks.[12]

Raven test. Each session starts with a computerized version of Raven's Standard Progressive Matrices test. The Raven test is a leading non-verbal measure of analytic intelligence [Carpenter et al., 1990; Gray and Thompson, 2004].[13] Each question of the test asks to identify the missing element that completes a visual pattern from a list of alternatives.[14] Out of five blocks of questions on the Raven test, we administer the three most difficult blocks (C, D, E) for a total of 36 questions. Subjects have 18 minutes to complete the test, 5 minutes for each of the blocks C and D, and 8 minutes for block E. Within each block, subjects can move back and forth between the questions, skipping some or changing their previous answers. Subjects earn 0.1 ECU for each correct answer.

Bomb risk elicitation task (BRET). Next, we administer the BRET, developed by Crosetto and Filippin [2013] to elicit subjects' risk aversion.[15] Possible payoffs range from 0 to 9.9 ECU.

School choice game. Subjects play repeatedly as students applying at schools under the Immediate Acceptance mechanism as described in Section 2.1. Overall there are 10 periods in which subjects apply; only one is selected randomly to determine payoffs. In each period, sixteen students, four for each preference type, are allocated seats at four schools with admission decisions depending on applicants submitted rank order lists and their lottery numbers, which are used to break ties. Subjects know their own preference type as well as the distribution of preferences when deciding on a rank order list to submit. Lottery numbers are drawn each period only after all subjects submit their lists. In each session subjects play five consecutive periods of the school choice game under each of the two preference profiles, i.e. under a fixed distribution of preferences, for a total of ten games. That is, we vary the preference profile *within* subjects. We vary the order of preference profiles P1 and P2 across sessions to control for order effects.

We vary *between* subjects the amount of feedback information they receive after each period of the school choice game. In sessions with No Information (NI), subjects are informed of their lottery draw, the school that they were admitted to, and the corresponding payoff in ECU. In sessions with Information (I) subjects are also informed on the number of applicants at each school in the first round of the mechanism—i.e. how many subjects ranked each school first. This information is also available to them when making a decision in the following period under the same preference profile.[16]

To avoid any correlation between cognitive ability and assigned preferences, we classify subjects as

[12] Appendix A includes screenshots of the decision screen for each task.

[13] Raven test scores are associated with the degree of strategic sophistication [Carpenter et al., 2013; Gill and Prowse, 2016], with the performance in Bayesian updating [Charness et al., 2013], and with more accurate beliefs [Burks et al., 2009].

[14] See Appendix A for an example.

[15] See Tables 7–9 in the Appendix where we use the measure as a control variable.

[16] Within the same project, we run sessions also under the deferred acceptance mechanism, with feedback identical to that of NI. Data are analyzed and reported in Basteck and Mantovani [2018]. All treatments were planned at the same time, so that no data was collected conditional on previous results.

TABLE 2: SESSIONS

Sessions	Date	Participants	Mechanism	Order	Info treatment
1–3	Sep 2015	16	IA	P1-P2	NI
4–6	Nov 2015	16	IA	P2-P1	NI
7–9	Feb 2016	16	IA	P1-P2	I
10–12	Feb 2016	16	IA	P2-P1	I

Notes: Order indicates whether the five rounds of preference profile 1 were run before (P1-P2) or after (P2-P1) preference profile 2. Info treat indicate whether the session was under No Information (NI) or Information (I). Six sessions with deferred acceptance as a mechanism (not reported here) where run between September and November 2015.

high and low ability based on their raven scores, using the session median as cutoff,[17] and assign two high and two low ability subjects to each preference type. Subject to this constraint, a new preference type is assigned randomly to each player in every new period.

2.3 Implementation

The computerized experiment was programmed using Z-tree [Fischbacher, 2007] and run at the WZB-TU Experimental Lab in Berlin between September 2015 and February 2016. It involved 192 subjects, distributed over 12 experimental sessions, where each subject participated only in one session. Sessions took on average around 80 minutes. Table 2 summarizes sessions' details.

All sessions followed an identical procedure. Subjects were randomly assigned to cubicles in the lab. Instructions were read aloud before each task.[18] To ensure everybody understood the tasks, subjects had to answer control questions before the BRET, and the school choice game. For the school choice game, this included an example where subjects had to find the allocation in a simple school choice problem, given submitted lists and lottery numbers. The tasks would only start after every subject had correctly answered all control questions. To get subjects used to the decision environment of BRET, we ran a trial round where no ECU could be earned, before running a single payoff-relevant round.

At the end of the school choice game, subjects were asked to complete a questionnaire. We gathered qualitative information about their strategies and their opinions regarding school choice. We also collected data on whether they had faced the Raven or a similar test before.

Subjects were told they would be paid according to the ECU earned in the Raven test, in the BRET and in one round of the school choice game selected at random by the computer. To determine payoffs in Euro, we applied the exchange rate: 1ECU= .70€. Subjects could earn between 0 and 14 Euros from the school choice game, between 0 and 2.52 Euros from the Raven test, and between 0 and 6.93 Euros from the BRET. The average payment, including 5 Euros of show-up fee, was 15.45 Euros.

[17] We break ties using the amount of time used to complete the Raven test. If ties still remain we break them at random.
[18] An English version of the experimental instructions is available in Appendix A.

3 Hypotheses

Identifying optimal strategies requires players to form correct beliefs about the strategies of opponents. In particular, it is important to know (*i*) how likely one is to be admitted if one first applies to a particular school and (*ii*) which school is still available in the second stage if one is initially rejected. For both these considerations, it is crucial to know the number of other applicants who rank the various schools first. Since in the information treatment last period's application numbers are known, we hypothesize that players are better able to identify optimal strategies in I than in NI, and play those strategies more frequently. For operational purposes, we define an optimal strategy as the best responses to the empirical distribution of opponents' strategies.

Hypothesis 1. *The frequency of best responses is higher in* I *than in* NI.

Section 2.1 predicts which strategies should be best responses. For preference profile P1, equilibrium predicts that both schools A and B will be overdemanded and hence filled in the first round. Thus, all players should rank C second and rank their favourite school first (i.e., Skip-the-Middle). For preference profile P2, equilibrium again predicts school A to be overdemanded so that a majority of players instead first applies at B or C. With fewer predicted applicants than B, school C is more likely to be available in round 2, so that players should rank it second, both when they first apply at A (Skip-the-Middle) and when they first apply at B (i.e., Skip-the-Top).[19] We can check whether the empirical best responses conform to these predictions.

Next consider the gap between applicants of low and high cognitive ability. Both schools A and B are likely to be filled after the first round and hence not be available in round two. As shown in Basteck and Mantovani [2018], absent any direct information on past applications, low ability subjects are less likely to rank C as a safe second choice, suggesting that they are less able to forecast first-round applications. High ability subjects on the other hand are better at playing best responses to the empirical distribution of strategies. We hypothesize that in I, where last period's application numbers are announced and the empirical distribution of strategies thereby partially revealed, the advantage of high ability subjects is reduced.

Hypothesis 2. *The difference in the frequency of best responses between low and high ability subjects is smaller in* I *than in* NI.

Following up on Hypothesis 2, we expect the payoff gap between high and low ability subjects to narrow once we provide more information. If information provision reduces the strategic mistakes by low ability subjects, we expect the treatment to be successful in reducing the payoff gap between low and high ability subjects.

Hypothesis 3. *The difference in payoffs between low and high ability subjects is lower in* I *than in* NI.

Strategic mistakes by low ability subjects induce ability segregation. By failing to rank C as a relatively safe second choice should they be rejected at their first choice, they instead apply to schools

[19] More formally, one can show that Skip-the-Middle and Skip-the-Top are the best replies when a fraction of naive players reports truthfully while other sophisticated players best respond.

that have no more (or very few) seats available in the second and third round of the mechanism are hence likely to be eventually assigned a seat at their least preferred school D. High ability subjects are then over-represented at school C, and low ability subjects are over-represented at school D. We hypothesize that, by reducing the strategic gap between subjects of different ability, information will also reduce ability segregation across schools.

Hypothesis 4. *Ability segregation is reduced in* I *relative to* NI.

4 Results

Observed outcomes depend to a large extent on realizations in the lottery. To avoid this confound, we estimate and compare expected payoffs and outcomes. For each profile in a given session and period, we simulate the matching n times, each time creating a new lottery ordering. We choose $n = 1000$ and consider the average payoff over the simulated matchings as the expected payoff of the corresponding subject in that period. We then apply the same procedure for all the other possible strategies of a subject, given the strategies in that period of the other participants in his session. The strategy that yields the highest expected payoff is their best response.[20]

The best response is Skip-the-Middle in 96 percent of the instances for preference profile P1, varying between 92 percent for type 4 and 98 percent for type 1. In P2, the best response is Skip-the-Middle in 85 percent of the instances for type 1. It is Skip-the-Top in 89 percent of the cases for type 2. The best response of type 3 is $A \succ C \succ B, D$ (i.e., truthtelling) two thirds of the times, and it is Skip-the-Top ($C \succ B \succ A, D$) 30 percent of the times. For type 4, the best response is Skip-the-Middle in 72 percent of the cases, and it is Skip-the-Top in 22 percent of the cases. Hence, in line with the equilibrium predictions reported in Section 2.1, P1 makes Skip-the-Middle an optimal strategy, while in P2 both Skip-the-Middle and Skip-the-Top are frequently best replies.[21] Since in both treatments there is no information on past applications in the first period, all reported statistics refer to the second to fifth period, i.e., where subjects receive additional information in I, unless indicated otherwise.

On aggregate, 19 percent of strategies are best responses in NI-P1, 34 percent in I-P1; 21 percent in NI-P2, 30 percent in I-P2. Wilcoxon rank-sum (WRS) tests on differences across treatments are shown in Table 3. Every test is based on one observation per session and exact p-values are reported. Significantly more best responses are submitted in I than in NI in both preference profiles, suggesting that the information helps applicants. Conversely, the rate of naive truth-telling is significantly lower in I. To ascertain that these differences are not due to a failure of the randomization of subjects across treatments, we check if the fraction of best responses differs across treatments in the first period, where the treatment should have no effect. Indeed, we do not detect any significant difference (WRS: P1: P-val$= .70$; P2: P-val$= 1.00$).

[20] Alternatively, one could adopt a recombinant estimation technique [e.g. Chen and Sönmez, 2006], which simulates allocations matching applications from different sessions. As suggested by one Reviewer, the technique is not recommended in our experiment, in particular because feedback is session-specific in I. Nevertheless, results are robust to the use of this technique and the corresponding analysis can be found in the previous versions of the paper.

[21] In contrast to the equilibrium predictions for P2, it is often possible to secure a seat at C in the second round, making it optimal for type 3 to report truthfully rather than to choose Skip-the-Top and rank C first.

TABLE 3: AGGREGATE ACROSS-TREATMENT DIFFERENCES

	Sample	Truthful % diff. (P-val)	Skip-the-Top % diff. (P-val)	Skip-the-Middle % diff. (P-val)	Best resp. % diff. (P-val)	Exp. Payoff % diff. (P-val)	Strat. cost % diff. (P-val)
I − NI	P1	**-33.9%** **(.01)**	-28.6% (.09)	**+81.3%** **(.02)**	**+74.3%** **(.03)**	+2.4% (.06)	**-36.9%** **(.01)**
	P2	**-36.9%** **(.02)**	**+88.7%** **(.02)**	**+110.7%** **(.05)**	**+40.2%** **(.05)**	**+3.8%** **(.00)**	**-48.2%** **(.00)**

Notes: the table reports, for each of the listed variables, the difference in the average between I and NI as a percentage of the value in NI, and the P-value of the corresponding Wilcoxon rank-sum test, for each preference profile. The (exact) statistic is computed using one observation per session. Expected payoff and best responses are computed simulating matchings under 1000 different lottery draws, and strategic cost is the difference between the expected payoff of the best response and the expected payoff of the chosen strategy. Bold indicates significance at the .05 level.

TABLE 4: WITHIN-TREATMENT DIFFERENCES BETWEEN HIGH AND LOW ABILITY SUBJECTS

	Treatment	Truthful % diff. (P-val)	Best resp. % diff. (P-val)	Exp. Payoff % diff. (P-val)	Strat. cost % diff. (P-val)
High − Low	NI-P1	-20.2% (.17)	**+327.5** **(.03)**	**+10.2%** **(.05)**	**-39.6%** **(.03)**
	I-P1	-22.9% (.35)	+71.7% (.06)	+8.5% (.09)	-36.5% (.16)
	NI-P2	-19.9% (.09)	**+134.1%** **(.03)**	**+4.9%** **(.03)**	**-28.1%** **(.03)**
	I-P2	-15.1% (.83)	+19.6% (.50)	**+6.9%** **(.03)**	**-41.4%** **(.03)**

Notes: the table reports, for each of the listed variables, the difference in the average between high and low-ability subjects as a percentage of the value for low-ability subjects, and the P-value of the corresponding Wilcoxon signed-rank test, for each preference profile. The (exact) statistic is computed using one observation per session. Expected payoff and best responses are computed simulating matchings under 1000 different lottery draws, and strategic cost is the difference between the expected payoff of the best response and the expected payoff of the chosen strategy. Bold indicates significance at the .05 level.

We conclude that, while players fall short of the equilibrium benchmark, disclosing information about past applications allows them to improve their choices of strategies, supporting Hypothesis 1.[22]

Result 1. *Subjects play a best response more frequently in* I *than in* NI.

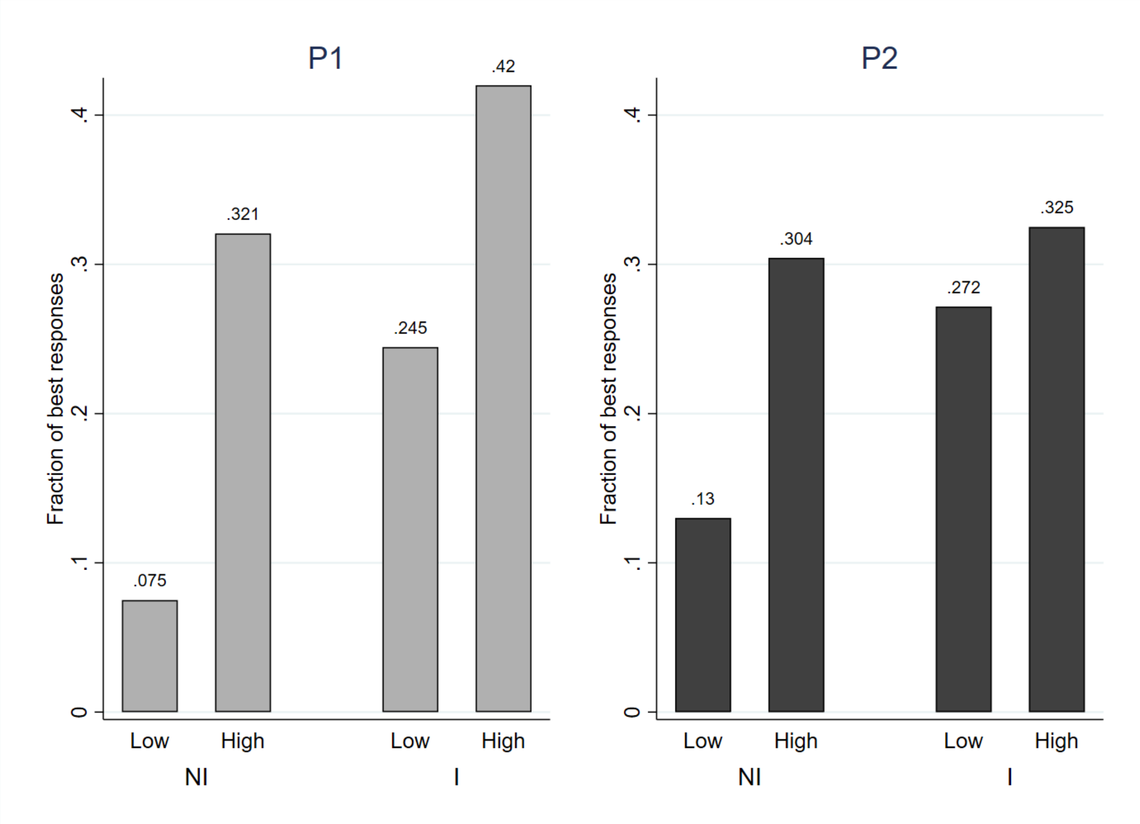
To analyze the effect of subjects' cognitive ability, we classify them as high or low ability depending on their Raven scores, using the whole-sample median as a cutoff.[23] The sample median is at a Raven score of 30, where 17 minutes and 57 seconds are used to complete the test. See Figure 8, Appendix B, for the complete distribution of Raven scores.[24]

[22] See also Table 6 in Appendix B.

[23] We break ties by time used to complete the test, where faster subjects are classified as high ability.

[24] In Basteck and Mantovani [2018] the threshold was slightly different, causing two subjects that were classified as high ability there to be classified as low ability here. Because of that, the statistics reported here for treatment NI will occasionally differ from the corresponding ones in Basteck and Mantovani [2018], despite the fact the data for that treatment are exactly the same.

Figure 1: Best responses by low and high ability subjects



Notes: fraction of best responses for top (High) and bottom (Low) half of the distribution of Raven scores, computed simulating matchings under 1000 different lottery draws.

Table 4 compares the observed strategy choices of low and high ability subjects by means of a Wilcoxon signed-rank (WSR) test that matches observed frequencies within each session. Low ability subjects report truthfully more often, but the difference is not significant in any individual treatment. Figure 1 shows the frequency with which low and high ability subjects choose a best response. In the no information treatment NI, high ability subjects use best responses significantly more often under both preference profiles; in treatment I the difference between high and low-ability subjects is still positive, but is not significant (see Table 4). High ability subjects are 4.3 times more likely than low ability subjects to play a best response in NI-P1 and 2.3 times in NI-P2. The figure reduces to 1.7 and 1.2 in I-P1 and I-P2. Table 5 shows non-parametric tests for the difference across treatments of the difference between the frequencies of best responses of high and low ability subjects. The corresponding diff-in-diff regressions are found in Table 7 in Appendix B. The difference decreases significantly in I-P2 compared to NI-P2. Regressions find a significant decrease also for P1 (at the .1 level), while the WRS test fail to reject the null. Considering, as an alternative metric, the variation across treatments in the ratio between the frequencies of best responses of high and low-ability subjects, WSR tests show a significant decrease in both preference environments (P1: exact P-val=0.05; P2: exact P-val=0.03). Overall, the evidence supports Hypothesis 2.

Result 2. *High ability subjects are more likely to play a best response. The gap between high and low*

TABLE 5: ACROSS-TREATMENT DIFFERENCES IN THE GAP BETWEEN HIGH AND LOW ABILITY SUBJECTS

		Top 50% vs Bottom%50		Top 20% vs Bottom%20	
		Best resp. difference	Exp. Payoff difference	Best resp. difference	Exp. Payoff difference
	Sample	% diff. (P-val)	% diff. (P-val)	% diff. (P-val)	% diff. (P-val)
$(\mathrm{I}_{high} - \mathrm{I}_{low}) - (\mathrm{NI}_{high} - \mathrm{NI}_{low})$	P1	-28.6% (.66)	-14.7% (.81)	**+172.1% (.01)**	+67.1% (.06)
	P2	**-69.5% (.04)**	+46.15% (.48)	-122.5% (.21)	-34.75 (.86)

Notes: the table reports for each of the listed variables the Wilcoxon rank-sum test, and corresponding P-value, on the difference between NI and I in the difference between high and low ability subjects (or top 20 vs bottom 20 %), within each preference profile. The (exact) statistic is computed using one observation per session. Expected payoff and best responses are computed simulating matchings under 1000 different lottery draws. Bold indicates significance at the .05 level.

ability subjects reduces significantly between NI *and* I.

We now turn to the implications of strategic choices for payoffs and student composition. The average expected payoffs are 9.28 in NI-P1, 9.51 in I-P1, and 9.76 in NI-P2, 10.13 in I-P2. In equilibrium, the corresponding figures would be 9.9 in P1, and 10.87 in P2. As the corresponding column in Table 3 shows, the increase in ex-ante expected payoffs between NI and I is statistically significant only in P2.[25] The last column in Table 3 considers a different metric: the cost of strategic mistakes, as measured by the difference between the expected payoff of one's best response, and the expected payoff of one's chosen strategy. WRS tests confirm that, on aggregate, I significantly reduces the cost subjects pay due to their strategic mistakes in both P1 and P2.

The gap in strategy choices between the two groups is reflected in their average expected earnings, as shown in Figure 2. Low ability subjects earn less in all treatments and the differences in expected payoffs are significant except for I-P1 (see Table 4). Perhaps surprisingly, the gap in expected payoffs does not decrease between NI and I (see Table 5).[26]

Result 3. *High ability subjects earn significantly higher payoffs than low ability ones in all treatments. The difference between the two groups does not decrease between* NI *and* I.

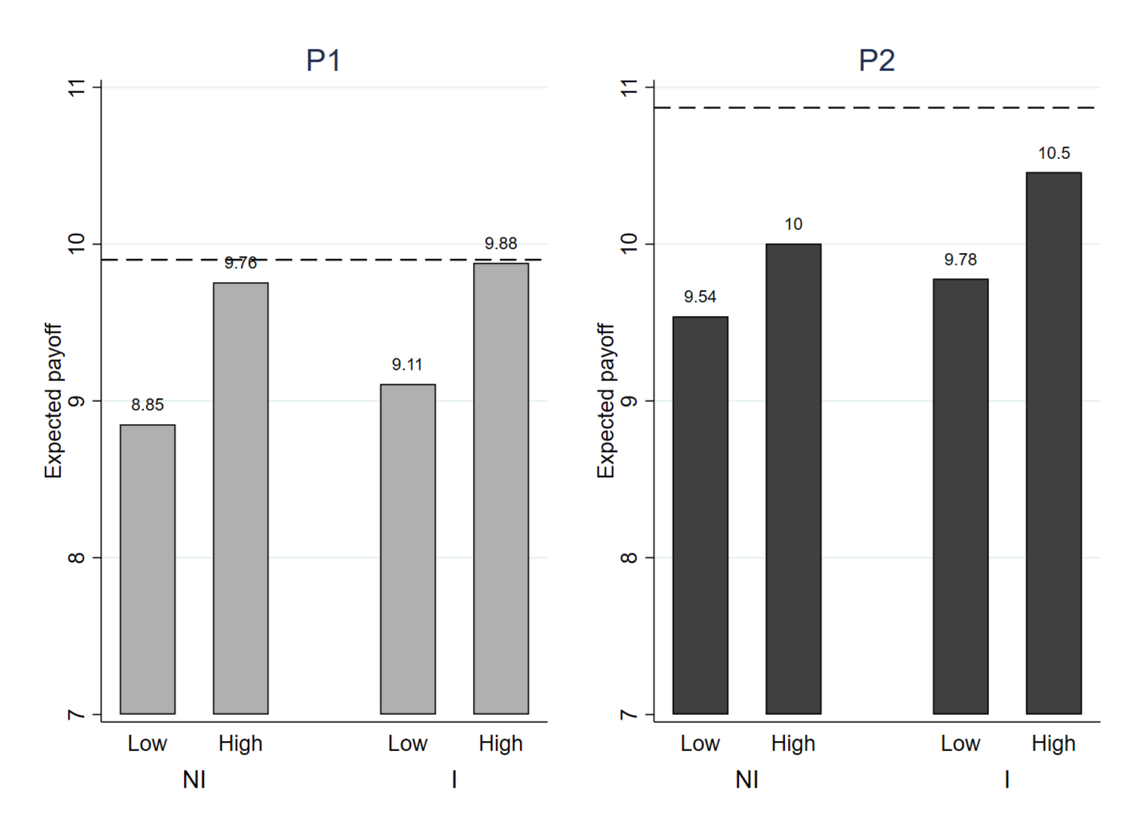
Hypothesis 4 states that ability segregation should decrease in I relative to NI. If high and low ability subjects play in a similar way, and since preferences are uncorrelated with cognitive ability by design, one expects high and low ability subjects to be evenly distributed over schools. Figure 3 reports the expected excess of high ability subjects at each school given the strategies used in the experiment. A positive value indicates that more high ability subjects are admitted at that school on average. A negative value indicates that more low ability subjects are admitted at that school on average.

For P1, figure 3 shows that in NI around 2.32 high ability subjects are admitted at school C, while only around 1.69 are admitted at school D. In other words, school C admits 37 percent more high ability

[25] See also Table 8, Appendix B, that finds an insignificant increase in I using regression analysis.

[26] See also the similar results obtained from regression analysis in Appendix B (Table 8 and top panels of Figure 10).

FIGURE 2: LOW AND HIGH ABILITY SUBJECTS' PAYOFFS



Notes: average expected payoffs computed for top (High) and bottom (Low) half of the distribution of Raven scores, computed simulating matchings under 1000 different lottery draws. Dashed lines = equilibrium payoffs.

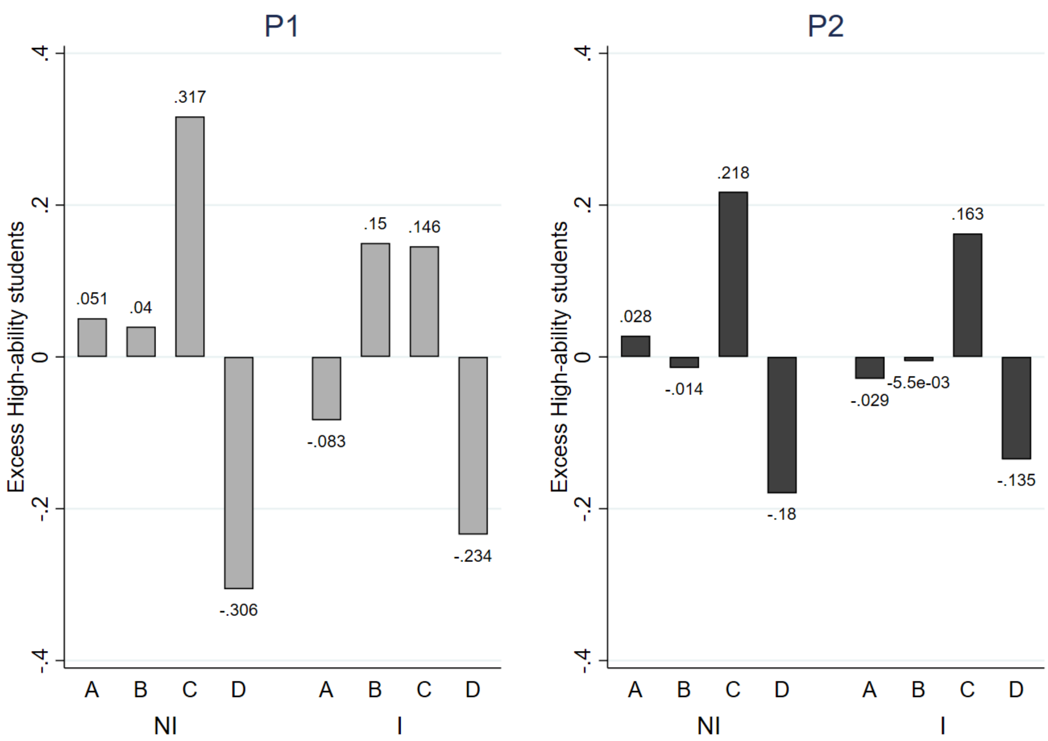
subjects than school D in NI. The same figure drops to around 21 percent in I. Similar patterns, though less marked, emerge in P2. We retrieve a measure of aggregate segregation by averaging over schools the absolute number of expected excess high ability subjects. This measure represents the average spread from the number of high ability subjects expected at each school under a uniform distribution. It allows to use session-level data and perform WRS tests as for the previous hypotheses. Alternatively, we can run a chi-squared test on the association between treatment and the distribution of subjects by ability at the different schools. The former approach rejects the null of equal segregation across treatments for both preference environments (P1: $Z = 3.32$, P-val$= .00$; P2: $Z = 2.57$, P-val$= .01$). The latter rejects the null that the distribution of ability at schools is independent from the treatment only for P1 (P1: prob=0.02; P2: prob=0.254).[27]

Result 4. *The distribution of high and low ability subjects at different schools is significantly closer to the uniform in* I *than in* NI *in* P1. *The evidence is mixed regarding* P2.

We find support for Hypothesis 2 and, at least partially, for Hypothesis 4, but not for Hypothesis 3: the gap in frequency of best responses between high and low ability subjects is reduced by providing information – however there is no corresponding reduction of the gap in expected payoffs. Figures 4 and 5 report the distribution of strategies adopted by low and high ability subjects, distinguishing between truthful reports and manipulated ones. Among the latter, we separate strategies that earn a

[27]For the corresponding parametric results see Appendix B, Table 10.

FIGURE 3: EXPECTED NUMBER OF HIGH ABILITY PEERS



Notes: The figure shows the expected excess of high ability subjects admitted at each school, relative to 2, given the empirical strategy distribution. For this statistic, low and high ability subjects are classified according to within-treatment medians, so as to obtain balanced treatments. Beyond this, the described recombinant strategies procedure is used.

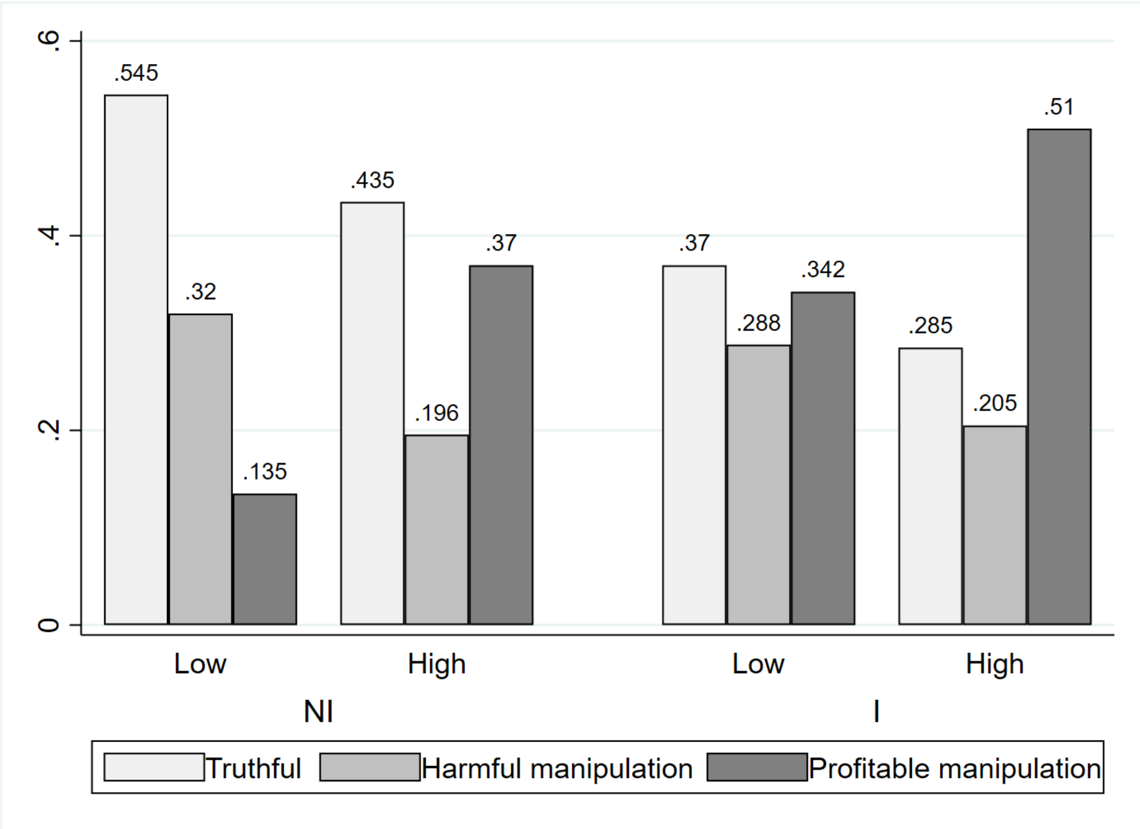
higher expected payoffs than truthful reporting ('Profitable manipulations') from strategies that earn a lower expected payoff than truthful reporting ('Harmful manipulations').

We have previously shown (see Figure 1) that in P1 the gap in best responses between low and high ability subjects reduces only in relative terms in I. Figure 4 reveals the presence of a second persistent gap: as shown by the difference in the use of harmful manipulations (see also the test statistics in Table 5), low ability subjects are more likely to harm themselves when choosing to misrepresent their preferences, both in NI and I. The fact that those mistakes increase in I also points to a potential side-effect of providing information, namely that this seems to induce more manipulations in general, including both profitable and harmful ones.

In P2, the provided information substantially reduces the gap in best responses (see Figure 1). Figure 5 shows once more the persistence of a second gap: even when they fall short of identifying a best response, high ability subjects use profitable manipulations more often than low ability ones, both in NI and in I. In Appendix B, Figure 11, we decompose the gap in payoffs between low and high ability subjects into its different strategic sources to further explain why the payoff gap does not reduce when providing information.

The multifaceted effect of information raises the question about potential heterogeneous effects of the treatment at different points of the distribution of cognitive ability. While information provision

FIGURE 4: STRATEGIES BY LOW AND HIGH ABILITY SUBJECTS: P1



Notes: distribution of strategies for top (High) and bottom (Low) half of the distribution of Raven scores. Correctly reporting one's preference ranking is labeled 'Truthful'. 'Profitable manipulations' include all strategies that earn a higher expected payoff than truthful reporting. 'Harmful manipulations' include all strategies that earn a higher expected payoff than truthful reporting.

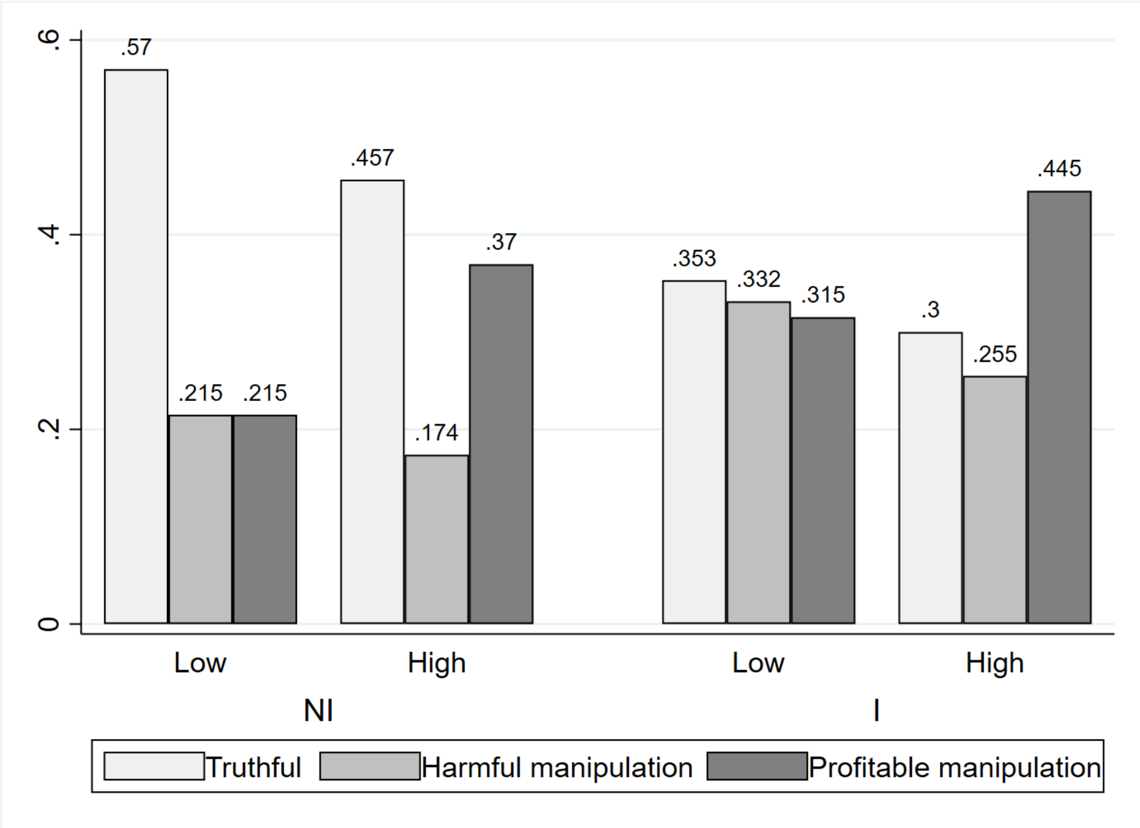
lifts the prospects of many subjects—including many that we classified as low ability—those in the left tail of the distribution of cognitive ability may be left behind and have their situation worsened. To check for this possibility, we compare the differences between the top and bottom 20 percent of the distribution of Raven scores. Results are shown in Table 5. The difference between these two groups widens significantly in I-P1 with respect to NI-P1 both in terms of frequency of best responses and of expected payoffs.[28,29]

Result 5. *The difference in the frequency of best responses and in expected payoffs between the top and bottom 20 percent of the distribution of cognitive ability increases significantly between* NI *and* I *in preference profile* P1.

[28]There seem to be some outliers in distribution of Raven scores (Fig. 8). These results are robust to the exclusion of subjects with a Raven score $\leqslant 10$ (computing the top and bottom 20 percent on the restricted sample): Wilcoxon rank-sum tests, difference in best responses, P1: $z = -2.14$, P-value= .03, P2: $z = .00$, P-value= 1.0; difference in expected payoff, P1: $z = -2.24$, P-value= .02, P2: $z = -.96$, P-value= .34.

[29]Regression analysis in Appendix B, Table 9 and bottom panels of Figure 10 confirm that the relation between Raven score and expected payoff is steeper in I than in NI.

FIGURE 5: STRATEGIES BY LOW AND HIGH ABILITY SUBJECTS: P2



Notes: distribution of strategies for top (High) and bottom (Low) half of the distribution of Raven scores. Correctly reporting one's preference ranking is labeled 'Truthful'. 'Profitable manipulations' include all strategies that earn a higher expected payoff than truthful reporting. 'Harmful manipulations' include all strategies that earn a higher expected payoff than truthful reporting.

5 Conclusions

Being admitted to a good school may have substantial effects on the educational achievement of children and their opportunities in life. Because of that, fairness and equity concerns play a central role in the choice of school allocation mechanisms. Theory and experimental evidence—including the one reported here—suggest that the immediate acceptance mechanism disadvantages applicants who are less able to game the system.

To level the playing field between applicants of different sophistication, theorists have proposed the use of strategy-proof mechanisms and various reforms have been implemented in that direction. However, there is accumulating evidence that even under such mechanism applicants misreport and that such (costly) mistakes are correlated with lower cognitive ability, lower educational attainment or socio-economic status [Chen and Pereyra, 2019; Guillen and Hakimov, 2017; Hassidim et al., 2017, 2016; Rees-Jones, 2018; Shorrer and Sóvágó, 2017].

A possible alternative is to aid applicants within the immediate acceptance mechanism by providing information that makes it easier to identify optimal strategies. If successful, such an approach would not only improve equity but also help to bring out the gains in efficiency that immediate acceptance can in theory provide. We show that, indeed, disclosing information about the number of past applications at schools allows applicants to make better decisions, in particular those in the lower half of the distribution of cognitive ability. As a result, ability segregation across schools is reduced. However, applicants at the very bottom of the ability distribution, seem less able to use the additional information and are left further behind; the gap in average payoffs between subjects of above and below median cognitive ability is unaffected.

Thus, making information about previous application periods more accessible can sustain the immediate acceptance's advantage in efficiency over the deferred acceptance and aid applicants of lower ability. However, in itself it is not sufficient to fully level the playing field between those who differ in their ability to identify optimal strategies, suggesting the need to explore further interventions, such as the adaptive immediate acceptance mechanism [Dur, 2019; Harless, 2014; Mennle and Seuken, 2017], which lets applicants apply at the next *available* school at each step of the algorithm, the 'Secure Boston Mechanism' [Dur et al., 2019], which secures applicants a seat at a school where they have sufficiently high priority initially, or the Chinese college admission mechanism studied by Chen and Kesten [2017].[30]

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[30]For this hybrid of IA and deferred acceptance, Chen and Kesten [2017] are able to show that it is less manipulable than IA, while dominating deferred acceptance in welfare terms given coarse priorities.

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A Experimental materials

Instructions

Welcome to this experiment in decision-making. You will receive 5 Euros as a show-up fee. Please, read carefully these instructions. The amount of money you earn depends on the decisions you and other participants make. In this experiment, on top of the show-up fee, you can earn between 0 and 26.30 Euro. In the experiment you will earn ECU (Experimental Currency Units). At the end of the experiment we will convert the ECU you have earned into Euro according to the rate: 1 ECU = 0.7 EURO. You will be paid your earnings privately and confidentially after the experiment. Throughout the experiment you are not allowed to communicate with other participants in any way. If you have a question please raise your hand. One of us will come to your desk to answer it.

TASK 1

On the sheet of paper on your desk you see a puzzle: a matrix with 8 graphic elements and an empty slot. There are eight possible numbered elements that could fill the empty slot. Only one is correct. Your task is to identify the element that correctly solves the puzzle. You choose the element you want by typing the corresponding number and pressing OK.

You will face 36 such puzzles, divided in three blocks of 12 puzzles each. Within each block, you can move back and forth through puzzles even without solving them, and change the answers you have given before. You have five minutes to complete blocks 1 and 2, and eight minutes to complete block 3. For each puzzle you correctly solve you earn 0.1 ECU. You will be informed about your score and earnings at the end of the experiment.

TASK 2

On the sheet of paper on your desk you see a field composed of 100 numbered boxes. You earn 0.1 ECU for every box that is collected. Every second a box is collected, starting from the top-left corner. Once collected, the box disappears from the screen and your earnings are updated accordingly. At any moment you can see the amount earned up to that point.

Such earnings are only potential, however, because behind one of these boxes hides a time bomb that destroys everything that has been collected.

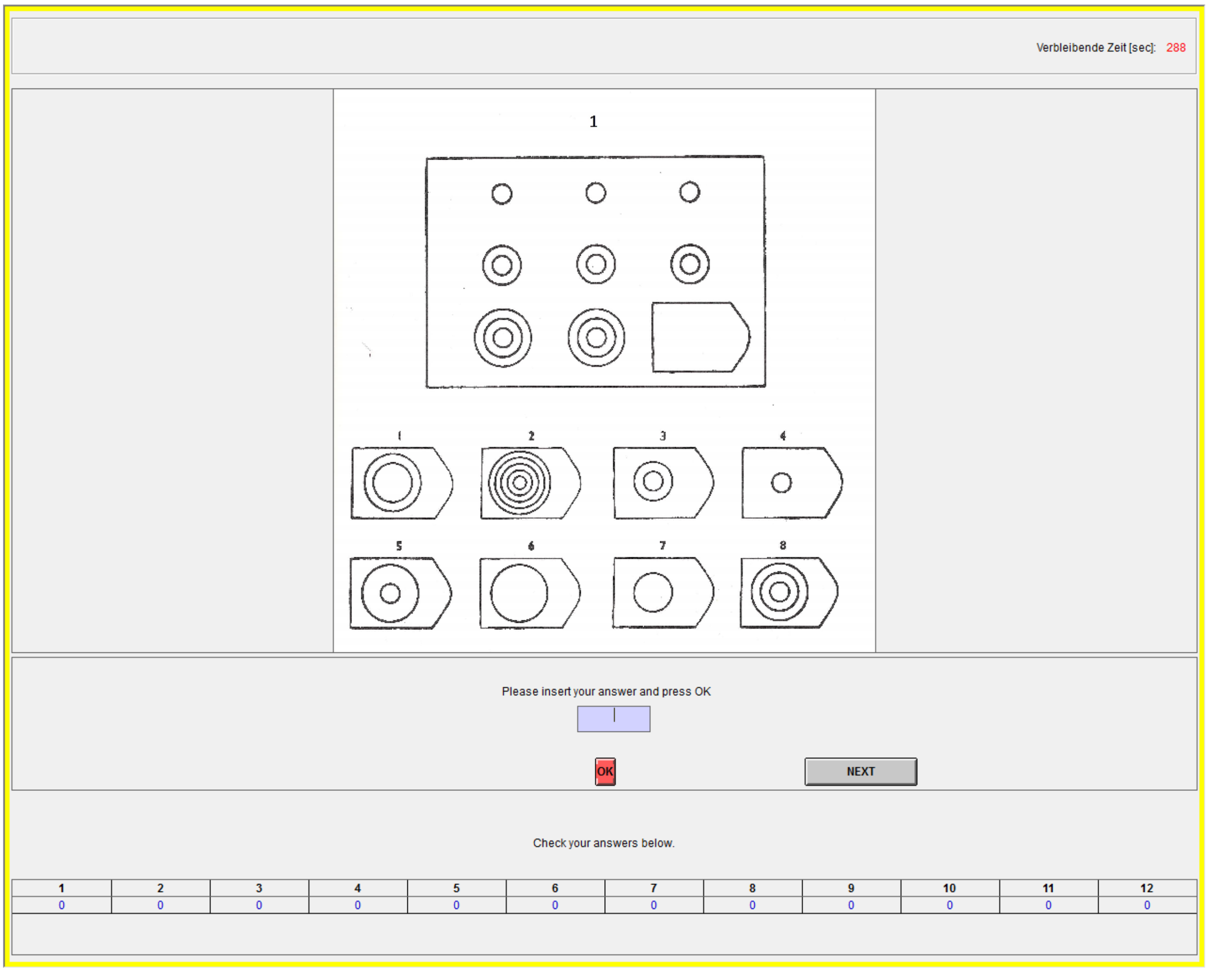
You do not know where this time bomb lies. You only know that the time bomb can be in any place with equal probability: the computer will randomly determine the number of the box containing the time bomb. Moreover, even if you collect the time bomb, you will not know it until the end of the experiment.

Your task is to choose when to stop the collecting process. You do so by hitting 'Stop' at any time.

If you happen to have collected the box where the time bomb is located, you will earn zero. If the time bomb is located in a box that you did not collect you will earn the amount of money accumulated when hitting 'Stop'. We will start with a practice round. After that, the paying experiment starts.

TASK 3

FIGURE 6: SCREENSHOT OF A QUESTION IN THE RAVEN TEST



In this part of the experiment, we model a procedure to allocate seats at schools to students. Each student has to submit an application form to apply for a seat at a school. You and the other participants take the role of students. An assignment procedure that we will explain in detail below, decides, based on the application forms submitted by you and the other 15 participants, who receives a seat at which school.

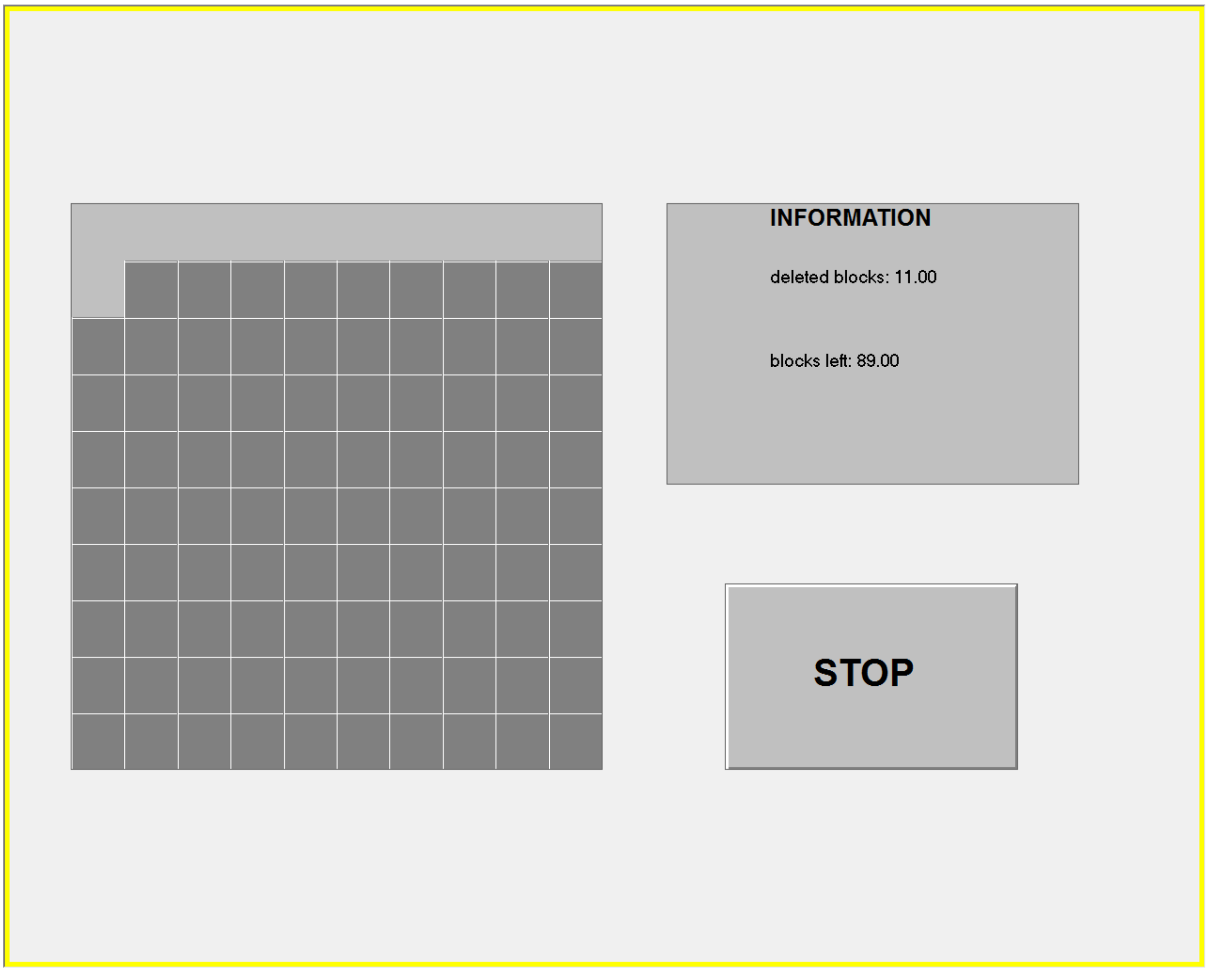
There are 10 Rounds, in which you will apply anew for a seat at a school. All rounds are independent: where you are admitted, depends only on the application forms submitted in this round. Your chances in the current round are not influenced by your own decisions or the decisions of other participants in previous rounds. At the end of the experiment, one round is selected randomly. Your payoff for Task 3 depends on the school that you have been admitted to in that round.

Earnings: rounds 1-5

In each round, you and the remaining 15 participants apply for one of 16 seats. These are distributed over 4 schools—A, B, C, D—where each school has 4 seats. The earnings of a student admitted at a school depends on his type. There are 4 types of students—1, 2, 3, 4—with 4 students of each type. The type of a participant will be randomly drawn in each round. The earnings of a student, depending on his type and the school the he is admitted to, are summarized in the table below.

You can read the table as follows: in a round where you are a student of type 2 and are admitted at

FIGURE 7: SCREENSHOT OF THE BOMB RISK ELICITATION TASK



ECU for a seat at school	A	B	C	D
Type 1	20	10	6	0
Type 2	16	17	6	0
Type 3	16	10	8	0
Type 4	16	10	6	0

school C you earn 6 ECU - if this round is chosen to be paid out, this amount will be converted to Euros and paid out at the end of the experiment. In the same way, a student of type 3 that is admitted at school A receives a payoff of 16 ECU.

The payoffs above remain unchanged for the first 5 rounds. In rounds 6-10, there is different payoffs table, which you will see on the screen.

Available decisions

In each round, you have to submit an application form. To do so, you have to fill in under ‘first choice’, ‘second choice’, ‘third choice’ and ‘fourth choice’ the name of the respective school: ‘A’,‘B’,‘C’ or ‘D’. This ranking determines the order with which your applications are sent to the schools, and, through the procedure outlined below, the school you are assigned to. You are free to choose the order in which you rank schools. When you are done, confirm your list by clicking ‘submit’.

The assignment procedure

Once all application forms have been submitted, each student draws a lottery number from 1 to 16: each number is drawn once. Each student has the same chances. For the assignment, students with a lower lottery number receive preferential treatment over students with a higher lottery number.

The assignment of participants to available seats works as follows:

phase 1:

- Application by students. Each student applies at the school that he ranked as first choice on his application form.

- Admission. If at most 4 students listed a school as first choice, all of them receive a seat at that school. If more students listed a school as first choice, than the school has seats, the seats at that school are given to the students with the lowest lottery numbers. Students, who receive a seat in phase 1 are admitted for good; for them, the assignment procedure is over. Applicants that do not receive a seat move to the next phase.

phase 2:

- Application by students. Every student, who has not been assigned a seat in phase 1, applies at the school that he ranked as second choice on his application form.

- Admission. If in the second phase there are at most as many applicants as free seats at the school, all of them receive a seat at the school. If there are more applicants than free seats, the remaining free seats are given to the students with the lowest lottery numbers. If there are no free seats left, no applicant receives a seat at the school. Students, who receive a seat in phase 2 are admitted for good; for them, the assignment procedure is over. Applicants that do not receive a seat move to the next phase.

phase 3:

- Application by students. Every student, who has not been assigned a seat in phases 1 and 2, applies at the school that he ranked as third choice on his application form.

- Admission. If in the third phase, there are at most as many applicants as free seats at the school, everyone receives a seat at the school. If there are more applicants in the third phase than free seats, the remaining free seats are given to the students with the lowest lottery number. If there are no free seats left, no applicant receives a seat at the school. Students, who receive a seat in phase 3 are admitted for good; for them, the assignment procedure is over. Applicants that do not receive a seat move to the next phase.

phase 4:

- Application by students. Every student, who has not been assigned a seat in phases 1, 2 and 3, applies at the school that he ranked as fourth choice on his application form.

- Admission. Since there are 16 applicants and 16 seats, there are as many free seats in phase 4 as applicants. Everyone receives a seat.

After every round you are informed about your lottery number and about the school where you received a seat. Then the next round starts.

Example

To illustrate the procedure described above, we consider an example. In this example, there are 8 students and 4 schools – V, W, X, Y – with 2 seats each to be assigned. Each Student draws a lottery number between 1 and 8.

student	Lottery number	First choice	Second choice	Third choice	Fourth choice
1	7	W	V	Y	X
2	5	V	W	X	Y
3	2	X	V	Y	W
4	8	V	X	Y	W
5	1	V	Y	W	X
6	3	X	W	Y	V
7	6	X	W	Y	V
8	4	V	Y	X	W

phase 1:

- Student number 1 applies at his first choice, school W. Since he is the only applicant there for two seats, he is accepted.
- Students number 2, 4, 5 and 8 apply at school V, that has only 2 seats available. The students with the two lowest lottery numbers (Student number 5 and 8) are accepted at school A. Students number 2 and 4 receive no seat in this phase.
- Students number 3, 6 and 7 apply at school X, that also has two available seats. Since there are more applicants than available seats, students with the lowest lottery numbers (students number 3 and 6) are accepted at X. Student number 7 receives no seat in this phase.
- The assignment procedure ends for students number 1, 3, 5, 6, and 8, who all received a seat at a school. Students number 2, 4 and 7 have received no seat in this phase and move to the next phase.

phase 2:

- Students number 2, 4 & 7 have no seat yet and apply at their second choice.
- Students number 2 and 7 apply at school W, where there is one free seat available. This is assigned to the student with the lowest lottery number (student number 2).
- Student number 4 applies at school X. There, there are no free seats.
- Students number 4 and 7 have received no seat in this phase and move to the next phase.

phase 3:

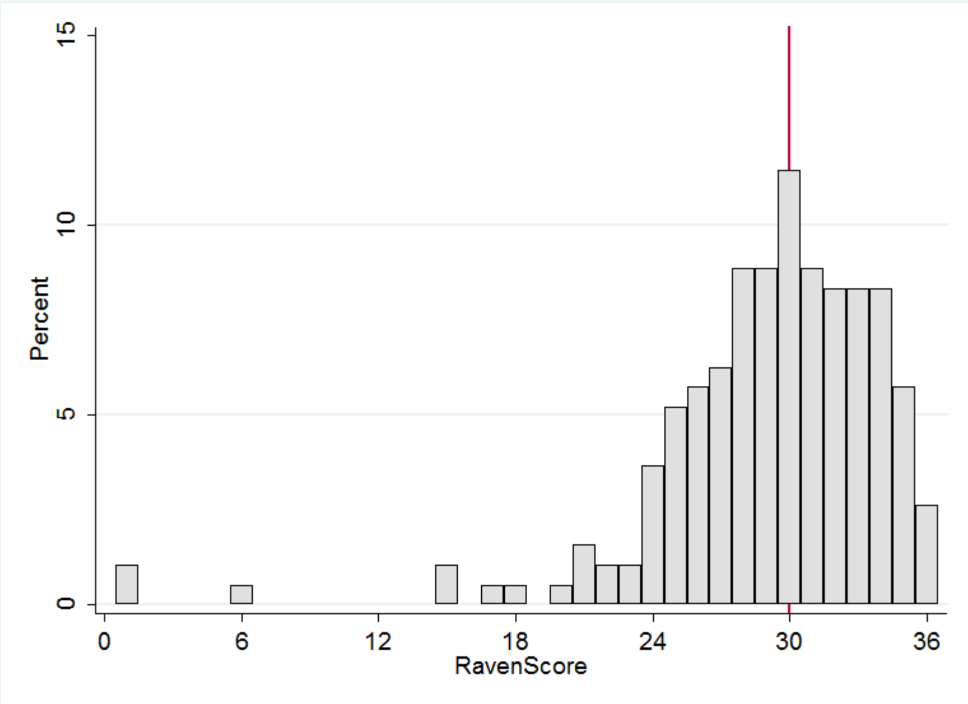
- Students number 4 and 7 apply at their third choice school, school Y, and are admitted, as school D has two free seats available. With this, the assignment procedure ends.

We arrive at the following assignment:

Student number	1	2	3	4	5	6	7	8
school	W	W	X	Y	V	X	Y	V

We start with a short quiz and an example. Then we begin with round 1.

FIGURE 8: DISTRIBUTION OF RAVEN SCORES



Notes: distribution of the number of correct answers to the 36 questions of blocks C, D and E of the Standard Raven Progressive Matrices. The dotted line denotes the sample median.

B Robustness checks and other empirical materials

Figure 8 shows the distribution of Raven scores in the experimental sample. Figure 9 shows the distribution of choices in the bomb risk elicitation task, together with the kernel densities of low and high ability ability subjects.

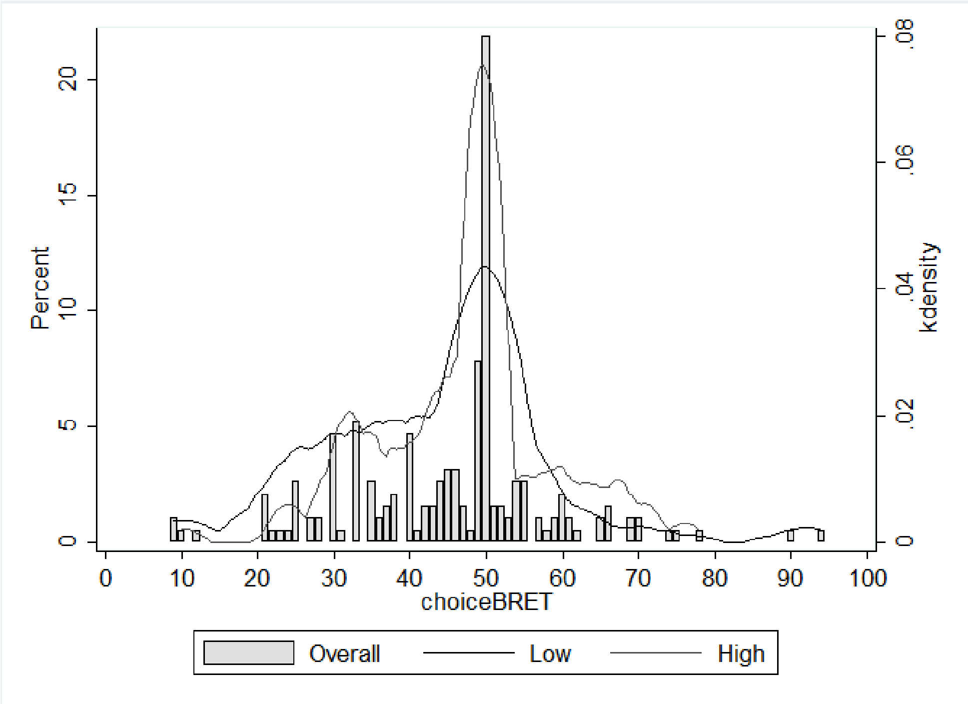
Table 6 presents regression analysis results on the determinants of best-responding behavior. It reports the marginal effects obtained from probit models, where the dependent variable is a dummy that takes value 1 if for that observation the subject plays a best response against the empirical distribution of others' strategies in his own treatment and period. The evidence is consistent with Result 1: the probability of best-responding is higher in treatment I.

Table 7 presents the result of a similar exercise investigating the interaction between the treatment and cognitive ability. Cognitive ability is measured as a dummy taking value 1 if a subject's Raven score is above the median of the experimental sample. The evidence is consistent with Result 2: the gap between subjects of high and low ability in the probability of choosing a best response is reduced when we provide additional information.

Table 8 reports regressions on the determinants of the expected payoffs. Models (1) and (4) confirm that the increase in payoffs across treatments is not significant. The coefficients of the interaction terms and the associated linear predictions, shown in the top panels of Figure 10, confirm that the reduction in the payoff gap between high and low ability subjects is not significant (Result 3).

Table 9 reports similar regressions, but instead of using a dummy for low/high cognitive ability, it

FIGURE 9: DISTRIBUTION OF RISK TASK CHOICES



Notes: distribution of the number of boxes collected in the Bomb Risk Elicitation Task. Below 50 = risk averse; above 50 = risk loving; 50 = risk neutral. Overimposed lines: kernel density estimations on the two samples of low ability subjects (below-median Raven score) and high ability subjects (above-median raven scores). The estimations employ the Epanechnikov kernel function and the bandwidth that minimizes the mean integrated squared error (under normality).

uses as regressor the Raven score, included as a continuous variable. The bottom panels of Figure 10 show the corresponding linear predictions. The evidence shows that the relation between one's Raven score and his expected payoffs is significantly steeper in I than in NI. This result is consistent with Result 5.

Table 10 reports the difference in the probability that high and low ability subjects have of being admitted at each school, and the corresponding tests of significance, based on the marginal effects obtained from a multinomial logit model. Under NI, we find high ability subjects are significantly more likely than low ability ones to be admitted at school C, and the converse holds for school D. The differences in these probabilities shrink in I. In particular, in both preference profiles low ability subjects are not significantly more likely to be admitted at school D, consistent with Result 4.

Finally, to further investigate the source of the gap in payoff in the different treatments, we decompose the average gap in expected payoffs into three components. First, part of the gap is due to the fact that high ability subjects best respond more often. If playing a best response rather than a suboptimal strategy would yield the same difference in expected payoff for any situation and any suboptimal strategy, this component would account for the whole difference between high and low ability subjects. Yet, the difference in expected payoff varies as best responses are more or less remunerative depending on the situation, i.e. on the player's preference type and on the precise distribution of opponents' strategies. This is captured by the second component. The third component captures the fact strategic mistakes may also yield different payoffs, depending again on the situation but also on the specific suboptimal

TABLE 6: INFORMATION AND PROBABILITY OF BEST RESPONDING: MARGINAL EFFECTS FROM PROBIT REGRESSIONS

	Dep. Var.: Pr(Best response)					
	P1		P2		Aggregate	
	(1)	(2)	(3)	(4)	(5)	(6)
I	0.190***	0.177***	0.111***	0.105***	0.150***	0.137***
	(0.054)	(0.047)	(0.042)	(0.041)	(0.038)	(0.034)
High		0.228***		0.155***		0.185***
		(0.048)		(0.041)		(0.034)
age		-0.017***		-0.006		-0.011***
		(0.006)		(0.005)		(0.004)
Period		-0.004		0.023*		0.010
		(0.013)		(0.014)		(0.010)
BRET		0.000		0.000		0.000
		(0.002)		(0.002)		(0.001)
Type 2		0.095**		0.002		0.042
		(0.047)		(0.050)		(0.034)
Type 3		0.041		-0.070		-0.019
		(0.045)		(0.047)		(0.032)
Type 4		-0.037		-0.114**		-0.085***
		(0.041)		(0.045)		(0.030)
order		-0.013		-0.016		-0.011
		(0.047)		(0.041)		(0.034)
female		-0.104**		0.004		-0.043
		(0.050)		(0.043)		(0.036)
Obs. (groups)	768 (12)	768 (12)	768 (12)	768 (12)	768 (12)	768 (12)

Notes: the table reports marginal effects obtained from panel probit regressions. In parentheses we report robust standard errors, clustered at the session level. *,**,***: statistically significant at the 10%, 5% and 1% level, respectively.'High' is a dummy for high ability subjects (i.e., above median Raven score).

TABLE 7: COGNITIVE ABILITY AND PROBABILITY OF BEST RESPONDING: MARGINAL EFFECTS FROM PROBIT REGRESSIONS

	Dep. Var.: Pr(Best response)					
	P1		P2		Aggregate	
	(1)	(2)	(3)	(4)	(5)	(6)
I	0.176***	0.172***	0.148***	0.157***	0.162***	0.163***
	(0.0379)	(0.0379)	(0.0411)	(0.0398)	(0.0280)	(0.0281)
High	0.230***	0.218***	0.169***	0.172***	0.200***	0.189***
	(0.0395)	(0.0395)	(0.0417)	(0.0413)	(0.0287)	(0.0288)
I*High	-0.071*	-0.069*	-0.127**	-0.151**	-0.089***	-0.092***
	(0.0310)	(0.0335)	(0.0628)	(0.0601)	(0.0442)	(0.0433)
age		-0.0142***		-0.00551		-0.00950***
		(0.00396)		(0.00348)		(0.00271)
period		-0.00922		0.0274**		0.0116***
		(0.0135)		(0.0135)		(0.00381)
choicebret		0.000911		0.00229		0.00174
		(0.00123)		(0.00123)		(0.000888)
Type 2		0.0643		0.0712		0.0635**
		(0.0445)		(0.0450)		(0.0315)
Type 3		0.00204		-0.0574		-0.0291
		(0.0426)		(0.0442)		(0.0310)
Type 4		-0.0531		-0.186***		-0.119***
		(0.0411)		(0.0384)		(0.0284)
order		-0.0154		-0.135***		-0.0756***
		(0.0307)		(0.0293)		(0.0215)
female		-0.0924***		-0.0131		-0.0551**
		(0.0327)		(0.0323)		(0.0233)
Obs. (groups)	768 (12)	768 (12)	768 (12)	768 (12)	1536 (12)	1536 (12)

Notes: the table reports marginal effects obtained from panel probit regressions. In parentheses we report robust standard errors, clustered at the session level. *,**,***: statistically significant at the 10%, 5% and 1% level, respectively. 'High' is a dummy for high ability subjects (i.e., above median Raven score).

Table 8: Payoffs for low and high cognitive ability: regression tables

	Dep. Var.: Expected payoff					
	P1			P2		
	(1)	(2)	(3)	(4)	(5)	(6)
I	0.187	0.274	0.324	0.367***	0.243	0.406***
	(0.119)	(0.238)	(0.223)	(0.104)	(0.156)	(0.120)
High	0.811***	0.898***	0.878***	0.601***	0.476***	0.683***
	(0.192)	(0.210)	(0.171)	(0.102)	(0.127)	(0.068)
I*High		-0.173	-0.238		0.249	-0.024
		(0.380)	(0.345)		(0.190)	(0.149)
age			-0.033			-0.033
			(0.021)			(0.022)
female			-0.216			0.018
			(0.158)			(0.162)
Type 2			0.983**			0.373
			(0.456)			(0.229)
Type 3			-1.407***			0.126
			(0.165)			(0.306)
Type 4			-1.906***			-1.721***
			(0.233)			(0.142)
Period			0.045			0.037
			(0.058)			(0.040)
order			-0.101			0.156*
			(0.108)			(0.088)
BRET			0.013			0.006
			(0.008)			(0.006)
_cons	8.915***	8.874***	9.650***	9.457***	9.517***	10.011***
	(0.142)	(0.162)	(0.740)	(0.103)	(0.111)	(0.705)
Obs (Groups)	768 (12)	768 (12)	768 (12)	768 (12)	768 (12)	768 (12)

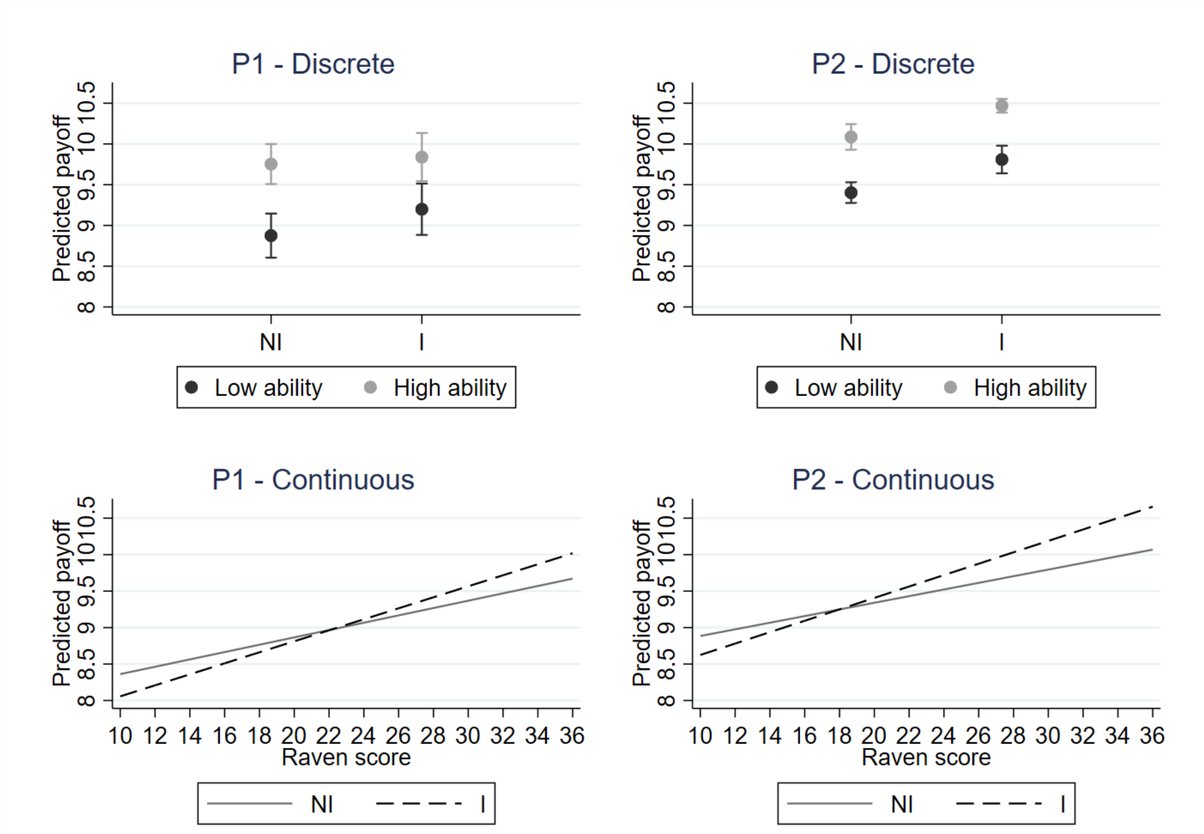
Notes: the dependent variable is computed using recombinant strategies procedure with 1000 recombinations for each subject in each period, and an identical number of tie breakers. In parentheses we report robust standard errors, clustered at the session level. *,** ,***: statistically significant at the 10%, 5% and 1% level, respectively. ‘High’ is a dummy for high ability subjects (i.e., above median Raven score).

TABLE 9: EXPECTED PAYOFF AND RAVEN SCORE: REGRESSION TABLES

	Dep. Var.: Expected payoff					
		P1			P2	
	(1)	(2)	(3)	(4)	(5)	(6)
I	0.166*	-1.136	-0.556	0.340***	-0.444	-0.587
	(0.091)	(1.107)	(1.103)	(0.086)	(0.762)	(0.647)
Raven	0.060***	0.044**	0.050***	0.057***	0.048***	0.046***
	(0.018)	(0.019)	(0.019)	(0.013)	(0.015)	(0.010)
I*Raven		0.045*	0.025*		0.027*	0.033*
		(0.028)	(0.017)		(0.016)	(0.021)
age			-0.035*			-0.034*
			(0.021)			(0.021)
female			-0.237			0.014
			(0.190)			(0.147)
Type 2			0.977**			0.378
			(0.454)			(0.231)
Type 3			-1.427***			0.131
			(0.156)			(0.306)
Type 4			-1.910***			-1.699***
			(0.221)			(0.149)
Period			0.045			0.037
			(0.058)			(0.040)
order			-0.102			0.160***
			(0.076)			(0.061)
Bret			0.012			0.005
			(0.008)			(0.006)
_cons	7.602***	8.039***	8.737***	8.120***	8.384***	9.115***
	(0.518)	(0.557)	(0.918)	(0.383)	(0.438)	(0.786)
Obs (groups)	768 (12)	768 (12)	768 (12)	768 (12)	768 (12)	768 (12)

Notes: the dependent variable is computed using recombinant strategies procedure with 1000 recombinations for each subject in each period, and an identical number of tie breakers. In parentheses we report robust standard errors, clustered at the session level. *,** ,***: statistically significant at the 10%, 5% and 1% level, respectively.

FIGURE 10: COGNITIVE ABILITY AND PAYOFFS: PREDICTIVE MARGINS FROM PANEL REGRESSIONS



Notes: predictive margins for the interaction between mechanism and cognitive ability. Top panels derived from models (3) and (6) of Table 8, comparing subjects with a below median Raven score against subjects above the median. Markers represent the average predicted expected payoff of a subject with low/high ability in each treatment, keeping all other covariates at the value they happen to take in the data. The difference between two markers within each treatment is the average marginal effect of having high cognitive ability. Bottom panels derived from models (3) and (6) of Table 9, regressing on the Raven score itself. They present the average predicted expected payoff of a subject with a specific Raven score in each treatment, keeping all other covariates at the value they happen to take in the data. The slope of each line is the average marginal effect of an additional correct answer in the Raven test.

strategy used.

Formally, let $\mathcal{L}$ be the set of observations of subjects of low ability, of cardinality n^L. Let $\mathcal{H}$ be the set of observations of subjects of high ability, of cardinality n^H.[31] Then, in each treatment, the gap is $\frac{1}{n^H}\sum_{i\in\mathcal{H}}\pi_i - \frac{1}{n^L}\sum_{j\in\mathcal{L}}\pi_j$. A subject with preference profile d that plays a best response in period t obtains an expected payoff that we can write as $\pi^{BR}_{d,t} = \delta^{BR}_{d,t} + \bar{\pi}^{BR}$, where $\bar{\pi}^{BR}$ is the average payoff of best responses. A subject with preference profile d that does not play a best response in period t obtains an expected payoff that also depends on the specific strategy s adopted by the subject, and that we can write as $\pi^{ERR}_{d,t,s} = \delta^{ERR}_{d,t,s} + \bar{\pi}^{ERR}$, where $\bar{\pi}^{ERR}$ is the average payoff of non-best responses. We

[31] Recall that we have ten observations for each subject, and that we use eight of these observations since we exclude the first period of each preference environment

TABLE 10: DIFFERENCES IN PROBABILITY OF ASSIGNMENT AT EACH SCHOOL

		School A	School B	School C	School D
High vs Low	NI-P1	.010 (.047)	-.042 (.029)	**.115** **(.029)**	**-.083** **(.038)**
	I-P1	-.021 (.033)	.042 (.034)	.031 (.034)	-.052 (.038)
	NI-P2	.063 (.043)	.021 (.048)	**.077** **(.048)**	**-.125** **(.027)**
	I-P2	.000 (.051)	.021 (.029)	.031 (.034)	-.052 (.044)
NI-P1 vs I-P1	Low	.016 (.029)	-.042 (.024)	.039 (0.21)	-.013 (.028)
NI-P2 vs I-P2	Low	.030 (.035)	-.001 (.028)	.004 (.027)	-.033 (.026)

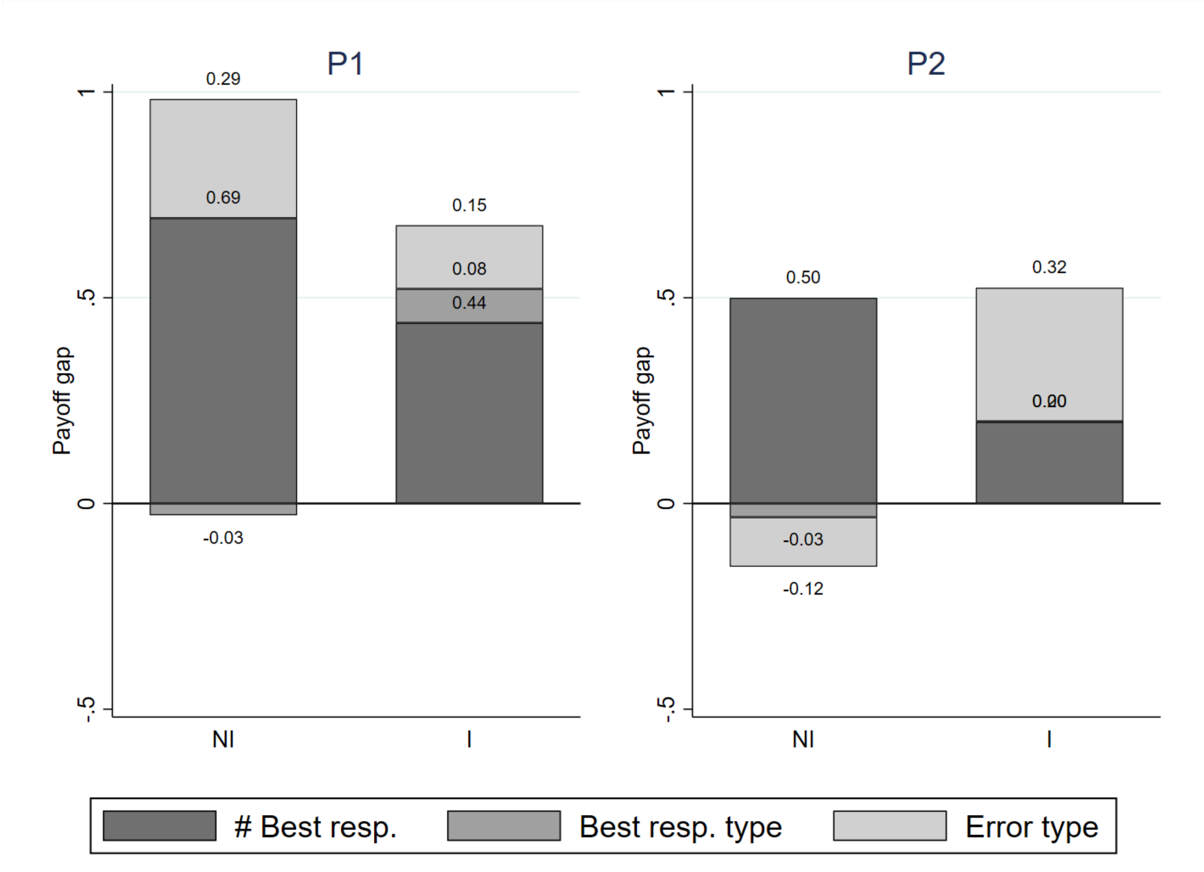
Notes: the table shows marginal effects estimated from a multinomial logit model. Robust standard errors in parentheses. Bold indicates significance at the .05 level. In the top panel, each cell can be interpreted as the difference between high and low ability subjects in the probability of being admitted at each school within each treatment; e.g., the probability that a high ability subject is admitted at school C under NI-P1 is 11.5 percentage points higher than that of a low ability subject (which means he is 1.5 times more likely to be admitted there). In the bottom panels, each cell can be interpreted as the difference in the probability of being admitted at each school between I and NI for low ability subjects; e.g., the probability that a low ability subject is admitted at school C under I-P1 is 3.9 percentage points higher than under NI-P1 (numbers for high ability subjects are, by construction, simply opposite in sign and are not reported)

then obtain:

$$
\begin{aligned}
\frac{1}{n^H}\sum_{i\in\mathcal{H}}\pi_i-\frac{1}{n^L}\sum_{j\in\mathcal{L}}\pi_j = {} & \left(\bar{\pi}^{BR}-\bar{\pi}^{ERR}\right)\left(\frac{n^{H,BR}}{n^H}-\frac{n^{L,BR}}{n^L}\right)\\
& +\sum_d\sum_t\delta^{BR}_{d,t}\left(\frac{n^{H,BR}_{d,t}}{n^H}-\frac{n^{L,BR}_{d,t}}{n^L}\right)\\
& +\sum_d\sum_t\sum_s\delta^{ERR}_{d,t,s}\left(\frac{n^{H,ERR}_{d,t,s}}{n^H}-\frac{n^{L,ERR}_{d,t,s}}{n^L}\right)
\end{aligned} \tag{1}
$$

The three components are represented in Figure 11. The improvement of low subjects in terms of number of best responses is evident, in particular in P2. However, it is outweighed by the fact that the remaining strategic gap is concentrated in situations where best responses are particularly advantageous and by the fact that low ability subjects make more calamitous mistakes whenever they fail to best respond. This evidence suggests that high ability subjects, not only best respond more often, but also make better use of the additional information in more intricate ways: to find a best response when this is most profitable or, at least, to avoid the most costly mistakes.

FIGURE 11: DECOMPOSITION OF THE EXPECTED-PAYOFF GAP



Notes: The figure decomposes the sources of the gap in expected payoffs between high and low ability subjects, for each treatment. '# BR' is the difference in the frequency of best responses between high and low ability subjects times the difference between the average payoff of best responses and the average payoff of non-best responses. 'BR type' is the sum over periods and preference types of the differences in the frequency of best responses between high and low ability subjects in each period/preference type times the spread between the payoff of a best response in that period/preference type and the average payoff of best responses. 'Error type' is the sum over periods, preference types, and strategies of the differences in the frequency of each strategy between high and low ability subjects in each period/preference type times the spread between the payoff of that strategy in that period/preference type and the average payoff of non-best responses.