Information Acquisition and Provision in School Choice: An Experimental Study*

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Abstract

When participating in school choice, students often spend substantial effort acquiring information about schools. We investigate how two popular mechanisms incentivize students' information acquisition in the laboratory. While students' willingness to pay for information is significantly greater under the Immediate than the Deferred Acceptance mechanism, most students over-invest in information acquisition, especially when they are more curious or believe that others invest more. Additionally, some students never invest in information acquisition but benefit equally from information provision. Both free provision and costly acquisition of information on students' own preferences increase their payoffs and allocative efficiency, whereas provision of information that helps students better assessing admission chances reduces wasteful investments. Our results also suggest that agents' information preferences, such as curiosity, can play an important role in market design theory and policy.

Keywords: information acquisition, information provision, school choice, experiment

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1 Introduction

> "It was very hard, and very time-consuming," one New Orleans resident said of trying to find a school for her daughter, who entered kindergarten last fall. "I'm educated, I have a bachelor's degree, ... and I do have time to read articles online and research things." – Arianna Prothero. 2015. "Parents Confront Obstacles as School Choice Expands," *Education Week*.

School choice is now part of the education landscape in the US. However, when choosing a school, students often have imperfect information about their own preferences regarding candidate schools, partly because it is difficult to assess the potential educational outcomes each school provides (Dustan, de Janvry and Sadoulet 2015). Unfortunately, acquiring this information can be costly if a student faces too many options or must acquire information about a number of factors, such as academic performance, teacher quality, school facilities, extra-curricular activities offered, and peer quality. In New York City, for example, the 600-page *Directory of NYC Public High Schools* covers nearly 700 programs at more than 400 schools citywide. Given this extensive information, students incur substantial costs in processing the information to rank up to 12 high school programs they would like to attend (Nathanson, Corcoran and Baker-Smith 2013). These information frictions can lead to substantial welfare loss (Narita 2016).

The cost of information acquisition is particularly harmful to low-income students. Indeed, research has shown that, due to limited information, low-income high achievers in the U.S. tend not to apply to selective colleges, in spite of the fact that generous financial aid makes these colleges more financially accessible than the colleges these students end up choosing (Hoxby and Avery 2013, Hoxby and Turner 2015). Informational intervention can therefore successfully convince many such students to apply to selective colleges (Hoxby and Turner 2013). Similar phenomena are observed among low-income families in public school choice (Hastings and Weinstein 2008).

Despite the documented information disparity, the matching literature typically assumes that all students have perfect knowledge about their own preferences, at least the ordinal ones. Relaxing this assumption, our study contributes to the literature by examining how different school choice mechanisms incentivize student information acquisition in the laboratory and how information provision can promote student welfare and allocation efficiency. Specifically, we focus on two widely-used mechanisms, the Boston Immediate-Acceptance (hereafter IA) and the Gale-Shapley Deferred-Acceptance (hereafter DA). By taking into account both the benefits and costs of information acquisition, this study provides a more comprehensive evaluation of the mechanisms and more tailored guidance for the design of school choice and other matching markets.

To explore behavioral regularities in information acquisition in matching markets, we conduct a laboratory experiment. It distinguishes information on one's own preferences from that on admission chances. The former is about a student's match value with each school, while the latter, captured by information on others' preferences in our setting, helps her better strategize. We then use the Becker-DeGroot-Marschak mechanism to elicit willingness-to-pay (WTP) for information (Becker, DeGroot and Marschak 1964).

We find that students' WTP for their own and others' preferences under the non-strategy-proof IA is significantly greater than that under the strategy-proof DA, consistent with the predictions in Chen and He (2018), a companion paper. However, there is significant heterogeneity in students' WTP. 15% of the students never invest in information acquisition (zero demand) and are thus disadvantaged by their lack of information, although they can use freely provided information efficiently. In contrast, most students' WTP is systematically higher than the theoretical prediction. Decomposing the WTP, we find that both conformity and curiosity explain students' over-investment in information acquisition. That is, a student tends to have a higher WTP when she expects a higher WTP by others (conformity)[1] or has a higher WTP for non-instrumental information (curiosity). These results further imply that information provision by educational authorities benefits zero-demand students as well as those over-investing in information acquisition (by reducing their wasteful investments). Surprisingly, reducing wasteful investments extends to others' preferences in DA under which students should have a zero WTP for such information.

These findings have several implications for market design research. First, a substantial fraction of the students have *information preferences*, such as curiosity and zero demand, that, if incorporated, may improve the empirical relevance of the models of information acquisition.[2]

Second, we present novel evidence on how the performance of DA is affected by information that can help students better assess admission chances. While prior literature indicates that providing such information decreases the truth-telling rate in strategy-proof mechanisms, we find that, in a setting with schools ranking students by a post-application lottery, the truth-telling rate does not change when such information is exogenously provided or endogenously acquired. Our proposed explanation is that truth-telling is the unique equilibrium strategy for (almost) all students in our setting but usually not in the previously studied settings.[3]

Lastly, on the methodological front, we create and implement a simple measure of curiosity

[1] In an equilibrium, a student has a lower WTP for information when others pay more. In other words, investments in information acquisition are strategic substitutes. We elaborate this point further in section 5.

[2] A typical model imposes the expected utility hypothesis; therefore, students do not have preferences for non-instrumental information, nor should they have zero demand for information that can increase their expected utility.

[3] Footnote 20 contains a precise statement regarding uniqueness.

and prove its relevance by showing that it accounts for a quarter of the WTP for information.

2 Literature Review

Our study on information acquisition contributes to the matching literature in which it is typically assumed that agents know their preferences perfectly (Gale and Shapley 1962, Roth and Sotomayor 1990, Abdulkadiroğlu and Sönmez 2003). Some recent theoretical papers study the effects of matching mechanisms on information acquisition, including Bade (2015), Harless and Manjunath (2015), Artemov (2016), Noda (2018), and Chen and He (2018). In particular, Grenet, He and Kübler (2019) and Immorlica, Leshno, Lo and Lucier (2020) study how a mechanism can provide more information on admission chances to facilitate information acquisition about students' own preferences; the former further provides evidence from university admissions in Germany.

Our study also contributes to the experimental literature on school choice which has focused on strategy, outcome, and welfare comparisons across mechanisms and has typically assumed that students know their own preferences (Chen and Sönmez 2006, Calsamiglia, Haeringer and Klijn 2010, Klijn, Pais and Vorsatz 2012, Featherstone and Niederle 2016). Hakimov and Kübler (2020) provide a recent survey of this literature. Our paper provides the first experimental evidence on information acquisition and provision in school choice.

Related to our study, Pais and Pintér (2008) investigate how various levels of information impact truth-telling, efficiency, and stability under the IA, DA, and Top Trading Cycles (TTC) mechanisms in a laboratory experiment of school choice. For each of the mechanisms, there are four information levels. The least informative condition, called "zero" information, has subjects' own preferences as private information but lacks a common prior and information on schools' priorities. Other information conditions provide more information that can help subjects better assess admission chances: subjects' own school priorities ("low" information), all subjects' school priorities ("partial" information), and preferences and priorities of all subjects ("full" information). They show that, across all three mechanisms, subjects are more likely to be truth-telling with zero information than with additional information, while there are no significant differences in truth-telling in any other pairwise comparisons across information conditions.[4] Their findings about DA can be explained by DA's multiple equilibria under all information conditions except zero, because of schools' pre-determined priorities. By contrast, truth-telling is the unique equilibrium for (almost)

[4]The same results are found in Pais, Pintér and Veszteg (2011). In a similar design, they study the effects of information on the performance of the same three mechanisms in a two-sided matching setting. The information conditions include zero, partial, and full information.

all subjects in our setting.[5] Therefore, our results about DA do not contradict theirs.

Recently, several experimental studies of school choice have examined peer information sharing within networks (Ding and Schotter 2016) or intergenerational (Ding and Schotter 2019) and top-down advice (Guillen and Hakimov 2018). In particular, Guillen and Hakimov (2018) run a field experiment to analyze truth-telling rates under TTC while providing a description of TTC, its properties, or both. They find that informing subjects of TTC's properties can increase the truth-telling rate when the information comes from a credible source.

We argue that information about subjects' actions can help them better assess admission chances. Related to sharing such information, computerized agents (robots) have been used in matching market experiments to better control the human subjects' strategic environment (Harrison and McCabe 1996, Guillen and Hing 2014, Guillen and Hakimov 2017, Chen, Jiang, Kesten, Robin and Zhu 2018). For instance, Guillen and Hakimov (2017) study subjects' truth-telling rates under TTC by grouping each subject with three robots to compete for school slots. They find that subjects have a higher truth-telling rate when they are told that robots are truth-telling.

Beyond the matching literature, information acquisition is examined in various settings, e.g., bargaining (Dang 2008), committee decisions (Persico 2004, Gerardi and Yariv 2008), contract theory (Crémer, Khalil and Rochet 1998, Crémer and Khalil 1992), coordination games (Hellwig and Veldkamp 2009, Szkup and Trevino 2015), finance (Barlevy and Veronesi 2000, Hauswald and Marquez 2006, Van Nieuwerburgh and Veldkamp 2010), and law and economics (Lester, Persico and Visschers 2009). In particular, there is a large body of theoretical literature on information acquisition in mechanism design/auction design, e.g., Persico (2000), Bergemann and Valimaki (2006), Compte and Jehiel (2007), Crémer, Spiegel and Zheng (2009), and Shi (2012).

While this literature is mostly theoretical, there are a few experimental investigations. For example, Gabaix, Laibson, Moloche and Weinberg (2006) conduct experiments with costly information acquisition to compare the directed cognition and fully rational models. Eliaz and Schotter (2007, 2010) evaluate agents' demand for non-instrumental information, which is closely related to our curiosity measure. Several studies report that subjects pay for non-instrumental information in the context of social learning (Kübler and Weizsäcker 2004, Çelen and Hyndman 2012, Goeree and Yariv 2015). In the auction literature, Choi, Guerra and Kim (2015) compare the second-price (sealed-bid) auction with the English auction when bidders have independent values and are heterogeneously informed, while Gretschko and Rajko (2015) compare the two auctions in relation to information acquisition and bidding behavior in an independent and private value environment. In

[5] Footnote 20 contains a precise statement regarding uniqueness.

comparison, Bhattacharya, Duffy and Kim (2017) study endogenous information acquisition in the context of voting behavior, whereas Page and Siemroth (2017) study information acquisition in an experimental asset market. Szkup and Trevino (2018) solve and test experimentally a global game of speculative attack where agents choose the precision of their private signal at a cost. In a field experiment on discrimination, Bartoš, Bauer, Chytilová and Matějka (2016) uncover differential information acquisition based on applicants' names. We will revisit these results in Section 5.

3 A Theoretical Framework

This section summarizes the main results from our companion theory paper (Chen and He 2018) on the endogenous acquisition of information about one's own and others' preferences under both IA and DA. These results form the basis for our experimental design and data analysis.

For completeness, we briefly introduce the setup here, with additional details in our theory paper and Appendix A. There are a finite set of students, I, to be assigned to a finite set of schools, S, through a centralized school choice mechanism. For each $s \in S$, there is a finite supply of seats, $q_s \in \mathbb{N}$, and the total capacity is no more than the total number of students, $\sum_{s \in S} q_s \leq |I|$, while $q_s > 0$ for all s. Moreover, schools rank students using a uniform random lottery (single tie-breaking) whose realization is unknown to students when they enter the mechanism.

Student i's von Neumann-Morgenstern utility of school s is $v_{i,s} \in [\underline{v}, \overline{v}]$, $0 < \underline{v} < \overline{v}$. Her cardinal preferences, $V_i = [v_{i,s}]_{s \in S}$, are an i.i.d. drawn from a joint distribution, F; her ordinal preferences are denoted by P_i. As such, we consider an independent-private-value model. Therefore, when acquiring information about others' preferences, a student aims to learn about the admission chance at each school to help her play the school choice game optimally.

We now define the two school choice mechanisms.

3.1 School Choice Mechanisms

We focus on two mechanisms popular in both the research literature and actual practice: the Boston Immediate Acceptance (IA) and the Gale-Shapley Deferred Acceptance (DA) mechanism.

IA asks students to submit rank-ordered lists (ROL) of schools. Together with the pre-announced capacity of each school, IA uses pre-defined rules to determine the school priority rankings for students and executes the following procedure:

Round 1. Each school considers all students who rank it first and assigns its seats in order of their priority at that school until either there is no seat left at that school or no such student left.

Generally, in:

Round $(k > 1)$. The kth choice of the students who have not yet been assigned is considered. Each school that still has available seats assigns the remaining seats to students who rank it as their kth choice in order of their priority at that school until either there is no seat left at that school or no such student left.

The process terminates after any Round k when either every student is assigned a seat at some school, or the only students who remain unassigned have listed no more than k choices.

DA can be either student-proposing or school-proposing. We focus on the student-proposing DA mechanism in this study. It uses information about the capacity of every school as well as students' ROLs of the schools in allocating seats. It utilizes strict rankings of schools over students using a pre-specified set of rules and proceeds as follows:

Round 1. Every student applies to her first choice. Each school rejects the least ranked students in excess of its capacity and temporarily holds the others.

Generally, in:

Round $(k > 1)$. Every student who is rejected in Round $(k - 1)$ applies to the next choice on her list. Each school pools together new applicants and those on hold from Round $(k - 1)$. It then rejects the least ranked students in excess of its capacity and temporarily holds the others.

The process terminates after any Round k when no rejections are issued. Each school is then matched with those students it is currently holding.

It is well-established that the student-proposing DA is strategy-proof (Dubins and Freedman 1981, Roth 1982), while IA is not (Abdulkadiroğlu and Sönmez 2003).

3.2 Information Acquisition and Provision in School Choice

Chen and He (2018) study information acquisition under the two mechanisms by introducing an information acquisition stage before the school choice game. We separately investigate the incentives to acquire one's own and others' preferences. For the former, the timing of the game is as follows, with more details in Figure A.1 of Appendix A.1:

(i) Nature draws student cardinal preferences V_i, and thus ordinal preferences P_i, from $F(V)$ for each i, but i knows only the distribution $F(V)$;

(ii) Student i invests $\alpha \in \mathbb{R}^+$ to acquire a signal on her own ordinal preferences that informs her the truth, P_i, or nothing; she is more likely to learn the truth with a larger α.

(iii) If P_i is learned, she then invests $\beta \in \mathbb{R}^+$ to acquire a signal on her cardinal preferences that informs her the truth, V_i, or nothing; a higher β reveals the truth more often.

(iv) Everyone knows that others engage in information acquisition, without knowing what they successfully acquire. Regardless of what information she has acquired, every student submits a rank-order list (ROL) of schools under either IA or DA as pre-announced.

The model differentiates between learning about ordinal and cardinal preferences, as the former only needs a student to acquire coarse information about the schools, whereas the latter requires her to acquire more detailed information but at a greater cost.[6] In our experiment, we simplify and combine these two types of information into one. We now summarize the first result.

Proposition 1 (Information acquisition incentives: Own preferences)**.** *In any symmetric Bayesian Nash equilibrium (with optimal investments α^* and β^*) under DA or IA, the following is true:*

(i) $\alpha^* > 0$, i.e., students always have an incentive to learn their ordinal preferences;

(ii) under DA, $\beta^* (P, \alpha^*) = 0$, $\forall P, \alpha^*$, i.e., there is no incentive to learn cardinal preferences;

(iii) under IA, there exists a preference distribution F such that $\beta^* (P, \alpha^*) > 0$ for some P, i.e., students have an incentive to learn their own cardinal preferences.

We next consider a student's incentive to acquire information about others' preferences, or, more precisely, information about admission chances. In reality, students may have interdependent values over schools, and thus information on others' preferences can help one learn about her own preferences. Here, we focus on information on others' preferences that is solely for strategic purposes or for assessing their admission chances at the schools.

To simplify the presentation, we assume that everyone knows her own cardinal preferences (V_i) but not others' preferences (V_{-i}), and that the distribution of V_i, $F(V_i)$, is common knowledge. To acquire information on V_{-i}, student i invests $\delta \in \mathbb{R}^+$ and learns the truth or nothing. This technology is described in Figure A.2 in Appendix A.1. We can now state our second proposition.

Proposition 2 (Information acquisition incentives: Others' preferences)**.** *In any symmetric Bayesian Nash equilibrium (with optimal investments δ^*) under a given mechanism, we have:*

(i) under DA, $\delta^* (V) = 0$ for all V, i.e., there is no incentive to learn others' preferences;

(ii) under IA, there exists a preference distribution F such that $\delta^* (V) > 0$ for V in some positive-measure set, i.e., some students have incentives to learn others' preferences.

In part (ii), the incentive under IA is present when students have sufficient conflicting interests, which characterizes most non-trivial school choice problems. For example, when many students have similar ordinal preferences, a student has incentives to know more about others' preferences,

[6] The literature on matching usually assumes that agents know their own ordinal preferences (Roth and Sotomayor 1990), but that cardinal preferences may be unknown due to "limited rationality" (Bogomolnaia and Moulin 2001).

as most of them compete for the same schools. In contrast, if one only likes a school that no one else is expected to like, knowing more about others' preferences does not help her.

Motivated by the above results, Chen and He (2018) also discuss the welfare implications of information provision. When an educational authority provides information on students' own preferences, student welfare in general improves. However, providing information on others' preferences has no effect under DA due to its strategy-proofness while having ambiguous effects under IA. These theoretical results guide our experimental design and hypotheses.

4 Experimental Design

To search for behavioral regularities in information acquisition in school choice while being guided by our theoretical predictions, we conduct a laboratory experiment in the simplest possible environment. Specifically, the value distribution simplifies information acquisition to a single step: upon learning one's own ordinal preferences, a student also learns her cardinal preferences.

Our goal is to compare student information acquisition behaviors under IA and DA and then to evaluate the welfare implications of various information-provision policies.

4.1 The Environment

There are three students, $i \in \{1, 2, 3\}$, and three schools, $s \in \{A, B, C\}$. Each school has one available slot and ranks students by a lottery. Student cardinal preferences are i.i.d. draws from the distribution in Table 1. Their preferences are also highly "correlated" in the sense that their values for schools A and C are identical and that a pair of students' ordinal and cardinal preferences are identical with probability 0.68. There is a single source of inefficiency: assigning school B to a student with a low value for B when there is at least one other student having a high value for B.

Table 1: Payoff Table for the Experiment

Students	$s = A$	$s = B$	$s = C$
$i \in$ {1,2,3}	100	10 with probability 4/5; 110 with probability 1/5	0

Notes: The above payoffs are in points. The exchange rate is 100 points = 1 USD.

Relative to real-life school choice problems, our environment is small, but it enables us to better identify key behavioral regularities that one may test in larger environments in future studies. We also note that many behavioral regularities identified in small games under DA or IA continue to manifest themselves in large games in the laboratory as demonstrated by Chen et al. (2018).[7]

Assuming that every student is an expected-utility maximizer, we solve all symmetric equilibria of the school choice game with information acquisition under either IA or DA for any given information structure. Derivations under the assumption that students are risk neutral or risk averse are relegated to Appendices A and B, respectively. To measure the incentive to acquire information about own preferences (denoted as "OwnValue"), we endow every student with the common prior that everyone knows only the preference distribution. For each student, we then calculate the payoff difference between knowing or not knowing one's own preferences, taking into account that the other two students may or may not know their own preferences. This difference is our theoretical prediction related to student's willingness to pay (WTP, henceforth) for their OwnValue. Similarly, to measure student WTP for information about others' preferences (denoted as "OtherValue"), we treat preference realizations as private information. For a given student, we derive the payoff difference between knowing or not knowing others' preferences. These results are summarized in the last two columns of Table 3.[8] Because the payoff difference depends on the number of other students who successfully acquire information, the predicted WTPs are sometimes an interval.

4.2 Treatments and Elicitation of WTP and Beliefs

Our experiment implements a 2 (mechanisms) $\times 2$ (information to be acquired) $\times$ 2 (information cost) factorial design to evaluate the performance of the two mechanisms under two information and cost conditions. The choice of the $2 \times 2 \times 2$ design is based on the following considerations.

(i) IA vs. DA (between-subject): DA is dominant-strategy incentive compatible, but not IA. Theoretically, each mechanism provides different incentives for information acquisition.

(ii) Acquiring OwnValue vs. OtherValue (between-subject): Our analyses suggest that the incentive to acquire information depends on the type of information that can be acquired.

(iii) Free vs. costly information acquisition (within-subject): While a free information condition enables us to evaluate information provision policies, a costly information acquisition condition better reflects reality. As this variation is implemented at the within-subject level, we also take into account the potential order effect: For half of the sessions, subjects first experience 10 free information rounds and then 10 costly information rounds (denoted as "free-to-costly"); for the other half of the sessions, subjects first experience costly information rounds and then free information rounds (denoted as "costly-to-free"). Furthermore, the

[7] They consider three game sizes: 4, 40, and 4000 students per game, with the last one using empirical robots.

[8] Relative to the case with risk neutrality, risk-averse students often have lower WTP for OwnValue and OtherValue. However, the same directional comparison between IA and DA maintains.

within-subject design feature allows us to evaluate whether a subject who under-invests in information can use information effectively when it is provided for free (section 5.3).

In the *free* information treatments, subjects are provided information about OwnValue (or OtherValue) at no cost. In comparison, in the costly information treatment, we use the Becker-Degroot-Marshak (BDM) mechanism (Becker et al. 1964) to elicit subject's WTP for their own or others' values of school B. Specifically, each subject is asked to enter her WTP for her own (or others') values in the interval, $[0, 15]$. The server then collects the WTP from each subject and generates a random number between $[0, 15]$ for each subject independently. If a subject's WTP is greater than the random number, she acquires the information and pays an amount equal to the random number; otherwise, she does not acquire the information and pays zero. The BDM procedure is incentive compatible under the assumption of monotonicity (Azrieli, Chambers and Healy 2018). To help subject understand the BDM mechanism, we provide subjects with numerical examples to illustrate and then test their understanding in a quiz at the end of the instructions. Our instructions for the BDM mechanism are adapted from those in Benhabib, Bisin and Schotter (2010).

To elicit each subject's belief about the average WTP of her two opponents, we use the binarized scoring rule (BSR) introduced by Hossain and Okui (2013). The BSR is incentive compatible under different risk attitudes and even when the decision maker is not an expected utility maximizer (Schotter and Trevino 2014). As such, it is more robust than alternatives, such as the quadratic scoring rule. In our use of the BSR, each subject submits a guess about the average WTP of the other two subjects. The server then computes the squared error between the guess and the actual average, i.e., SE = (guess $-$ actual average)^2. Next, the server randomly draws a number, R, uniformly from $[0, U]$. If SE $\leq$ R, the subject receives a fixed prize of 5 points. Otherwise, she receives zero points. Based on our pilot sessions, we find that 90% of the squared errors fall at or below 49. Therefore, we use 49 as the upper bound in our BSR calculation, i.e., $U = 49$. The random number, R, is drawn independently for each subject, and for each round.

Our experimental instructions (Appendix C) explain DA and IA to subjects in detail, and we include an example in the Review Questions to test subject understanding of the mechanisms. Following the convention in experimental economics, we do not inform the subjects of their optimal strategies under either mechanism. Specifically, we do not tell subjects that truth-telling is a dominant strategy under DA, which allows us to examine their naturally emerging strategies.

4.3 Experimental Procedures

Each experimental session consists of 20 rounds with costly (free) information for the first ten rounds, and free (costly) information for the next ten rounds. The order is counterbalanced for each treatment. Each session consists of 12 subjects.

At the beginning of each session, every subject is randomly assigned an ID number and is seated in front of a computer terminal. The experimenter then reads aloud the instructions for the first ten rounds. After this, subjects have the opportunity to ask questions, and answers are provided to the full group. Subjects are then given ten minutes to read the instructions at their own pace and to answer the review questions. After ten minutes, the experimenter distributes the answers and go over them with the group. Afterwards, subjects go through ten rounds of the experiment, randomly re-matched into groups of three at the beginning of each round. After the first ten rounds, the experimenter reads the instructions for the second ten rounds aloud and answers any questions in public. Subjects again complete a set of review questions, and then go through the second ten rounds of the experiment. For example, in the acquiring OwnValue treatments, each round consists of the following two stages:

Stage 1: Playing the game without the information on own value:

(i) Each subject is provided with the value distribution (Table 1) to induce the common prior.

(ii) Each subject is asked to rank the schools. The server then collects the rankings, draws the school-B value for each subject, generates the tie-breaker, and allocates schools to subjects. The allocation outcomes are shared with subjects at the end of each round.

Stage 2: Playing the game with free information or the possibility to acquire information about own value:

(i) The server draws a new set of values for every subject. Everyone acquires her value for school B, either for free or by paying a cost:

  (a) For the *free* information treatment, everyone receives her own school-B value for free.

  (b) For the *costly* information treatment, we use the BDM mechanism to elicit each subject's WTP. We tell the subjects that everyone will know the number of other subject(s) in her group who observe their value(s), regardless of whether she will observe her own value or not.[9] The server collects the reported WTP and generates a random number between $[0, 15]$ for each subject. Incentivized by the BSR, each subject submits a guess

[9] This design implies that the elicited WTP is only for OwnValue and does not include the incentive to learn the number of other subjects who observe their values. Note that the number of others who receive information is needed for computing one's WTP for information (see Appendices A and B).

of the average WTP of the other two subjects in her group. The server collects the guesses and generates another random number between $[0, 49]$ for each subject.

(ii) Afterwards, each subject receives the following feedback on her computer monitor:

   (a) *Free* information treatment: her school B value and the fact that every subject in her group is provided with their own value.

   (b) *Costly* information treatment: her WTP, her random number for WTP, her guess, her random number for her guess, the number of other subjects in her group who observe their values, and the WTPs of the other subjects in her group.

(iii) Each subject is then asked to rank the schools. The server again collects the rankings, generates a new tie-breaker for each subject, and allocates the schools.

(iv) When a round ends, each subject receives the following feedback on her computer monitor: her ranking, her value, the tie-breaker, her allocation, and her payoff.

The *OtherValue* treatments proceed in a similar way, except that each subject always knows her own value for school B before ranking schools. The information provided or acquired is the other two subjects' values for school B.

After 20 rounds, we implement the Holt and Laury lottery choice procedure to elicit subjects' risk attitudes (Holt and Laury 2002). In addition, after telling each subject her payoff from the risk elicitation task, we offer an opportunity for subjects to acquire information about the realization of the lottery, again using the BDM mechanism. Their WTP for this information is a measure of their *curiosity*, defined as an intrinsic demand for information that has no instrumental value (Grant, Kajii and Polak 1998, Golman and Loewenstein 2015). As risk preference measurement is prevalent in both laboratory and field experiments, our curiosity measure can be easily implemented together with almost any risk preference elicitation method. We view this simple and novel measure of curiosity as a methodological contribution to the literature.

At the end of the experiment, each subject fills out a demographic and strategy survey on the computer and is then paid in private. Each experimental session lasts approximately 90 minutes. The average payment is \$27.89, including a \$5 show-up fee. The experiment is programmed in z-Tree (Fischbacher 2007).

Table 2 summarizes the features of the experimental sessions. For each treatment, we conduct three independent sessions at the Behavioral Economics and Cognition Experimental Lab at the University of Michigan. As mentioned, each session consists of 12 subjects. No subject participates in more than one session. This design gives us a total of 24 independent sessions and 288 distinct subjects. In the process of conducting experimental sessions, we found a coding error in

Table 2: Features of Experimental Sessions

Information to Be Acquired	Immediate Acceptance order	Immediate Acceptance # of subjects	Deferred Acceptance order	Deferred Acceptance # of subjects
OwnValue: Own Preferences	free-to-costly	3×12	free-to-costly	3×12
	costly-to-free	3×12	costly-to-free	3×12
OtherValue: Others' Preferences	free-to-costly	3×12	free-to-costly	3×12
	costly-to-free	3×12	costly-to-free	3×12

Notes: Each session, with 12 subjects, has 10 rounds with free information and another 10 rounds with costly information. For any given treatment, sessions with free information rounds first are denoted as "free-to-costly"; and the others with costly information first are denoted as "costly-to-free".

our z-Tree program in the second ten rounds of the experiment in the DA-OtherValue (free-to-costly) treatment, i.e., a subject's own value was not provided in the second ten rounds. In this case, we use the data from the first ten rounds for these three sessions in our data analysis, since the instructions and program for the first half are both correct. With these three additional sessions, we have a total of 27 independent sessions with 324 subjects. Our subjects are University of Michigan students, recruited using ORSEE (Greiner 2015). Experimental instructions are included in Appendix C; the data are available from the authors upon request.

5 Experimental Results

This section focuses on subjects' WTP for information and their welfare in the game under various information structures. We use some shorthand notations in presenting the results. First, $x > y$ denotes that a measure under treatment x is greater than that under treatment y, statistically significantly at the 5% level. Second, $x \geq y$ denotes that a measure under x is greater than that under y but insignificant at the 5% level. The summary statistics of the key variables are in Table D.1 of Appendix D, and we relegate the analysis of the rank-order lists of schools to Appendix D.4.

5.1 Willingness to Pay for Information

As predicted theoretically, subjects' WTP for their OwnValue of school B should be greater under IA than under DA in the experiment (Appendix A). Intuitively, information acquisition pays off only when a subject learns that she has a high value for B. In this case, she will top rank B under either mechanism. IA gives her a better chance of obtaining B because she only competes for B with others who also top rank B; by contrast, she likely competes with everyone for B under DA.

Figure 1 depicts the time series of the average WTP for OwnValue, with the theoretical predictions for risk neutral subjects represented by the horizontal dashed lines. Our predictions are often intervals, because one's WTP depends on the number of others having acquired information, which is uncertain when the subject reveals her own WTP. Figure 1 shows that, while the average WTP for OwnValue under IA is mostly within the theoretical bounds, it is substantially above the prediction under DA. Moreover, the average WTP is lower for the subjects whose first ten rounds give them free information, indicating the importance of learning or order effect (costly-to-free vs. free-to-costly). We examine these empirical regularities further in subsequent subsections.

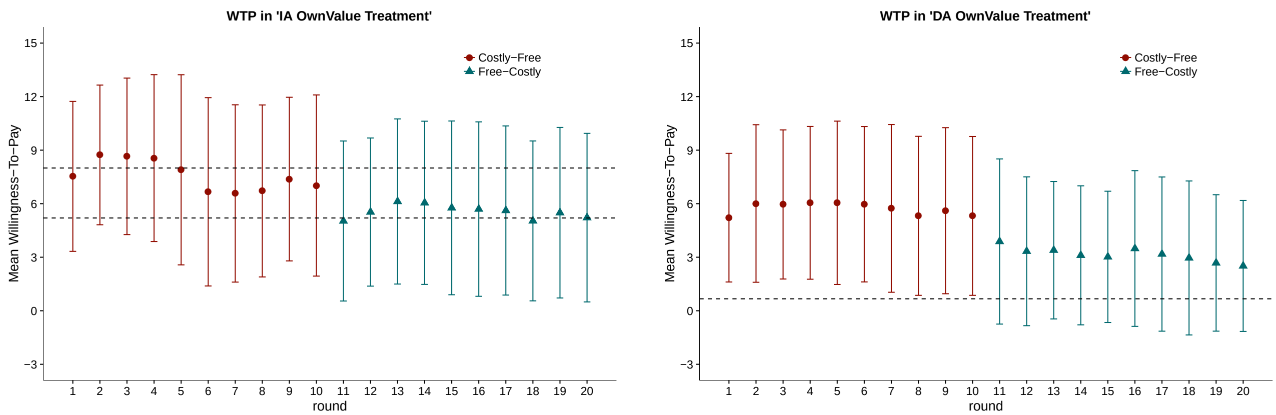

Figure 1: Average WTP for Own Value by Rounds

Notes: The dashed lines denote the theoretical predictions for the WTP of risk-neutral subjects. Error bars represent one standard deviation. WTP data is only available in the first ten rounds of costly-to-free sessions (i.e., costly information acquisition rounds played before those with free information) and the last ten rounds of free-to-costly sessions (i.e., free information rounds played before those with costly information acquisition).

The first three columns in Table 3 present the session average WTPs, with the corresponding standard deviations in parentheses, whereas the last two columns provide the theoretical predictions for risk-neutral and risk-averse subjects for each treatment, respectively. In most cases, we find that risk aversion predicts a lower WTP in our environment.

We now present our first hypothesis about WTP for OwnValue and the corresponding result.

Hypothesis 1 (WTP for OwnValue)**.** *A subject's WTP for OwnValue under IA is greater than it is under DA; both are positive. That is, IA $>$ DA $>$ 0.*

Result 1 (WTP for OwnValue)**.** *A subject's WTP for OwnValue under IA is significantly greater than it is under DA; both WTPs are positive.*

Support: Table 3 presents the session average WTP for each treatment. Taking each session as an independent observation, we reject the null of no difference in favor of Hypothesis 1 that IA $>$ DA ($p = 0.03$, one-sided Wilcoxon rank-sum test). Furthermore, the average WTP for OwnValue under IA is 6.56 (s.d. 4.78), while that under DA is 4.44 (s.d. 4.38). Both are significantly different from zero at the 1% level. ∎

Table 3: Average Willingness-To-Pay for Information by Treatment

Treatment	All six Sessions	Free-to-Costly Sessions	Costly-to-Free Sessions	Theoretical Prediction	
				Risk Neutral	Risk Averse
IA OwnValue	6.56	5.56	7.57	[5.2, 8]	[4.9, 7.7]
	(4.78)	(4.59)	(4.75)		
IA OtherValue	4.51	4.00	5.02	[0, 0.24]	[0, 0.46]
	(4.55)	(4.55)	(4.49)		
DA OwnValue	4.44	3.16	5.72	0.67	[0.3, 0.4]
	(4.38)	(4.05)	(4.33)		
DA OtherValue	2.21	1.90	2.52	0	0
	(3.16)	(3.25)	(3.04)		

Notes: The WTPs are measured in experiment points. There are six sessions in each treatment, three sessions with free information rounds first (denoted as free-to-costly) and the other three with costly information first (denoted as costly-to-free). Standard deviations are in parentheses and are calculated by treating each subject-round outcome as one observation. Therefore, for each treatment, there are 720 observations from the 10 costly rounds for these 72 subjects, half of which are from the costly-to-free treatments, while the other half are from the free-to-costly treatments.

We next examine a subject's WTP for information about others' preferences. Figure 2 depicts the time series of the average WTP for OtherValue, again, with the theoretical predictions for risk-neutral subjects depicted by the horizontal lines. Our subjects exhibit a substantially greater WTP than our predictions with either risk neutrality or aversion. We summarize our theoretical predictions in the following hypothesis and then present the corresponding result.

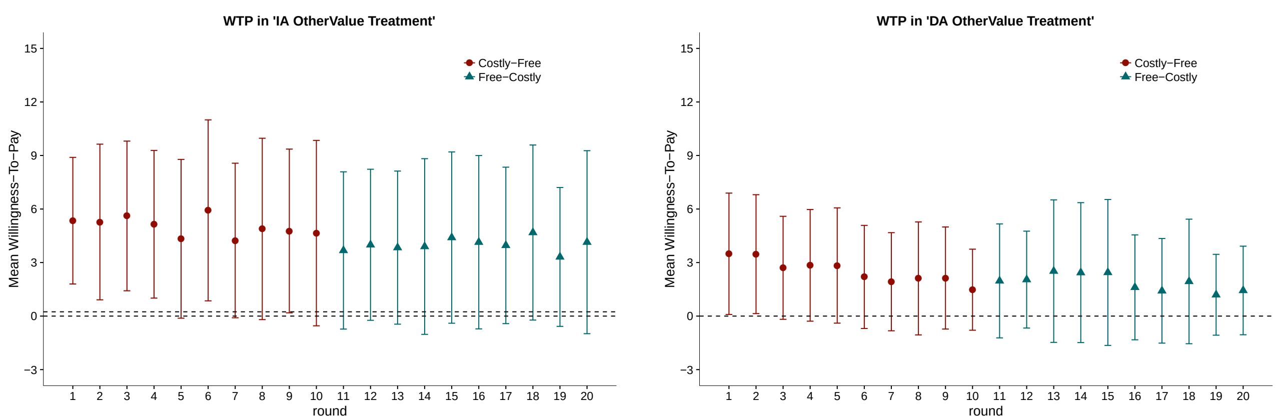

Figure 2: Average WTP for Others' Values by Rounds

Notes: The dashed lines denote the theoretical predictions for the WTP of risk-neutral subjects. Error bars represent one standard deviation. WTP data is only available in the first ten rounds of costly-to-free sessions (i.e., costly information acquisition rounds played before those with free information) and the last ten rounds of free-to-costly sessions (i.e., free information rounds played before those with costly information acquisition).

Hypothesis 2 (WTP for OtherValue)**.** *A subject's WTP for OtherValue is zero under DA regardless of risk attitude, whereas it is positive under IA. Therefore, IA $>$ DA $=$ 0.*

Result 2 (WTP for OtherValue)**.** *A subject's WTP for OtherValue under IA is significantly greater than it is under DA, but both are significantly different from zero: IA $>$ DA > 0.*

Support: Table 3 presents the average WTP for OtherValue in each treatment. Treating each session as an independent observation, we reject the null of no difference in favor of Hypothesis 2 that a subject's WTP for OtherValue follows IA > DA ($p = 0.01$, one-sided Wilcoxon rank-sum test). Furthermore, the average WTP for OtherValue under IA is 4.51 (s.d. 4.55), while that under DA is 2.21 (s.d. 3.16). Both are significantly different from zero at the 1% level. ∎

The low WTP for OtherValue in DA shows that the theoretical predictions has some bite. Additionally, under either IA or DA, a subject's WTP for OwnValue is significantly greater than that for OtherValue ($p = 0.01$, one-sided Wilcoxon rank-sum test), consistent with our predictions.

In sum, the directions of our WTP comparisons across mechanisms and across OwnValue and OtherValue are consistent with theory. However, subjects often exhibit an access WTP or over-investment for information relative to equilibrium predictions. Similar over-investments has been observed in other endogenous information acquisition experiments in the context of jury or committee voting (Bhattacharya et al. 2017), private value auctions (Gretschko and Rajko 2015), as well as prediction markets (Page and Siemroth 2017).[10]

As excess WTP for information has important welfare implications, it is crucial to understand its determinants. To do so, we rely on a variety of subject traits, such as curiosity, risk preferences, and conformity. In the following, we first examine the determinants of WTP at the subject level (section 5.1.1) and then in panel regressions (section 5.1.2). Based on these findings, we decompose the observed WTP into the effects of behavioral and cognitive factors (section 5.2). Lastly, we investigate the behavior of those who never invest in information acquisition (section 5.3).

5.1.1 Determinants of WTP for Information: Subject-Average

We first investigate the determinants of WTP for information at the subject level. Because the elicited WTP is censored below at 0 and above at 15, we use the following Tobit model to analyze the determinants of the observed subject average WTP, denoted by $\overline{WTP}_i$:

$$\overline{WTP}_i^* = X_i'\beta + \varepsilon_i, \text{ and } \overline{WTP}_i = \max\{0, \min\{\overline{WTP}_i^*, 15\}\},$$

[10]Bhattacharya et al. (2017) explain their observed over-investment as a result of a combination of poor strategic thinking and the quantal response equilibrium model; Gretschko and Rajko (2015) explain the over-investment with regret avoidance. Page and Siemroth (2017) find that their subjects tend to acquire more information if they have larger endowments, existing inconclusive information, lower risk aversion, and less experience in financial markets.

where ε_i is normally distributed; X_i is a vector of independent variables and controls; and only a censored version of the latent variable $\overline{WTP}_i^*$ is observed, denoted by $\overline{WTP}_i$. In the data, $\overline{WTP}_i$ is the average of subject i's WTPs from all rounds and is censored for 18% of our main sample (43 out of 241 consistent subjects, defined below).[11] Our independent variables include the four treatment dummies and demographics. Furthermore, we control for the following variables:

(i) **% playing a dominated strategy w/ free info under DA/IA**: This variable measures the fraction of times a subject plays a dominated strategy in the free information rounds. Under IA, a dominated strategy is top ranking school C; under DA, it is not reporting true ordinal preferences.[12] As such, this variable is negatively correlated with a subject's understanding of the mechanism. We expect that confusion about the mechanism could lead to sub-optimal information acquisition, but we are agnostic about the direction.

(ii) **Costly-to-free**: This dummy variable indicates that a session follows the costly-to-free order. Playing the game with costly information acquisition in the first ten rounds imposes a higher cognitive load as subjects must simultaneously learn both the school choice game and the information acquisition game. Moreover, one may learn through the free-information rounds the true value of information.

(iii) **Curiosity**: This variable measures a subject's curiosity using her WTP for the lottery realization in the Holt-Laury risk elicitation task. As such information is non-instrumental, this WTP reflects a subject's "curiosity," or general preference for information.

(iv) **Risk aversion**: Risk aversion is measured as the switching point in the Holt-Laury lottery choice menu. Following the literature, we define a *consistent* subject as one who exhibits a single switching point and chooses the right column in the last lottery choice. In our sample, 241 of the 288 subjects (84%) are consistent; among them, 78% are risk-averse, 16% risk-neutral, and 7% risk-loving. Theoretically, a greater degree of risk aversion is associated with a lower WTP for information (see Appendix B). Intuitively, in our environment, WTP for information is a cost incurred with certainty and determined by the utility difference between the uncertain outcomes associated with the two information sets. Risk aversion, implying a concave utility function, makes the difference smaller in terms of certainty equivalent.

In the following, again, we first state our hypothesis and then discuss our results.

[11] In a robustness check, we find similar results in linear models (see Table D.2 in Appendix D).

[12] Among the consistent subjects, as Table D.1 shows, the proportion of dominated strategy play is 0.9% (0.6%) in the IA OwnValue (OtherValue) treatment; the proportion is 8.5% (7.4%) in the DA OwnValue (OtherValue) treatment, lower than that in prior laboratory experiments on DA. In a survey of experiments on matching markets, Hakimov and Kübler (2020) report that the average proportion of dominated strategy play is 30% when subjects rank three schools under DA. Dominated strategy play in DA might reflect that DA is not obviously strategy-proof (Li 2017).

Hypothesis 3 (Curiosity, Risk Aversion, Order Effect, and Dominated Strategies)**.** *Subjects, who are more curious, less risk averse, in the costly-to-free treatments, or play dominated strategies more often, have a higher WTP for OwnValue and OtherValue.*

Table 4 presents the results for the four Tobit specifications investigating the determinants of subject-average WTP. Column (1) includes the results for our full sample, whereas columns (2)-(4) include only consistent subjects, progressively adding more controls.

While the treatment effects estimated from the Tobit model are largely consistent with Results 1 and 2, this set of analyses uncovers additional findings. First, the variables, "% playing a dominated strategy with free info" and curiosity, are each positively correlated with WTP. However, the positive correlation between playing a dominated strategy under IA and WTP is not statistically significant, possibly because only 8% of the subjects ever play a dominated strategy under IA. Furthermore, the timing of the information acquisition game in the experiment matters. That is, subjects exhibit a higher WTP when costly-to-free $= 1$. Several explanations are consistent with this order effect, e.g., cognitive load, learning, and anchoring.[13] Lastly, consistent with our theoretical prediction, we find that subjects with a greater risk aversion exhibit a lower WTP (column 3); however, risk aversion becomes insignificant once we include demographic controls (column 4). We summarize our findings below.

Result 3 (Curiosity, Risk Aversion, Order Effect, and Dominated Strategies)**.** *Subjects who are more curious, less risk averse, in the costly-to-free treatments, or play dominated strategies under DA more often, have a significantly higher WTP for OwnValue and OtherValue.*

5.1.2 Determinants of Willingness to Pay for Information: Panel Data Analyses

We next explore within-subject time-series variations using panel regressions on the subject-round observations. Compared to the analysis of the subject average WTP in section 5.1.1, panel regressions exploit the i.i.d. draws of subject values for school B in each round and investigate the dynamics of subject WTP within a session. Based on our theoretical analysis (Appendix A), we formulate the mechanism effect on incentives to acquire information as Hypothesis 4.

[13] This order effect is consistent with previous experimental findings that a higher cognitive load can cause suboptimal play (Bednar, Chen, Liu and Page 2012). Alternatively, subjects can learn that information is not as useful as they might have thought after receiving it for 10 rounds in the free-to-costly treatment. We thank an anonymous referee for suggesting this explanation. Another explanation for this order effect is anchoring. That is, if a subject receives information on her own or others' values for school B for free for the first ten rounds, she starts with an anchor of zero, which might in turn lower her WTP for the second ten rounds when information is no longer free. We thank Yeon-Koo Che for suggesting this explanation.

Table 4: Determinants of Subject-Average WTP: Tobit Model

	(1) Full Sample	(2) Sub-sample	(3) Sub-sample	(4) Sub-sample[a]
IA_OwnValue	6.45***	6.26***	5.20***	3.33
	(0.56)	(0.57)	(1.12)	(4.06)
IA_OtherValue	4.32***	4.05***	3.48***	1.33
	(0.62)	(0.72)	(1.22)	(4.19)
DA_OwnValue	4.13***	3.78***	3.05***	1.09
	(0.71)	(0.82)	(1.11)	(3.98)
DA_OtherValue	1.47***	1.01**	1.03	-0.81
	(0.45)	(0.47)	(1.17)	(4.04)
% playing a dominated strategy w/ free info (in percentage points)[b]				
IA			0.13	0.12
			(0.10)	(0.11)
DA			0.07***	0.07***
			(0.02)	(0.02)
Curiosity			0.34***	0.34***
			(0.05)	(0.05)
Costly-to-free			1.94***	1.87***
			(0.46)	(0.36)
Risk Aversion			-0.30**	-0.24
			(0.14)	(0.16)
Female				-0.91**
				(0.44)
Graduate Student				0.49
				(1.93)
Black				-1.52
				(1.45)
Asian				-0.78*
				(0.44)
Hispanic				-2.88**
				(1.11)
$\#Subjects$	288	241	241	241
$\#Clusters$	24	24	24	24

Notes: The outcome variable in all regressions is the subject-level average WTP for information. The regressions do not include a constant. There are 42 (out of 241, or 17%) subjects with an average WTP $= 0$ and one subject with WTP $= 15$. Columns 2–4 include only consistent subjects in the Holt-Laury lottery game. Column 4 also includes the following controls: age, ACT score, SAT score, dummy for other non-white ethnicities/races, dummy for ACT score missing, dummy for SAT score missing, dummy for degree missing, dummy for age missing, dummy for ethnicity missing, and dummy for gender missing. Standard errors clustered at the session level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
a. A treatment dummy's coefficient represents the average WTP in that treatment with all other control variables being zero. To see if two treatments have different average WTPs, we test if the two corresponding coefficients are equal. For example, in column (4), any pair of treatments have a WTP difference significant at the 5% level, except for IA_OtherValue and DA_OwnValue. In columns (1)–(3), the difference between every pair of treatments is significant at the 1% level.
b. "% playing a dominated strategy w/ free info" (in percentage points) is defined as the percentage of times a subject plays a dominated strategy in rounds without information acquisition. Under IA, a dominated strategy is top ranking school C; under DA, a dominated strategy is not reporting true ordinal preferences. Among the consistent subject, those in the IA OwnValue and OtherValue treatments has a mean $= 0.8$ percentage points (s.d. $= 3.2$, $n = 120$, with 110 of them having this variable equal to zero); those in the DA OwnValue and OtherValue treatments have a mean $= 8.0$ percentage points (s.d. $= 13.8$, $n = 121$, with 57 of them having this variable equal to zero).

Hypothesis 4 (Mechanism Effect & Highe-B Value)**.** *(i) A high value for school B does not increase a subject's WTP for OtherValue under DA; however, (ii) it should increase a subject's WTP for OtherValue under IA.*

The intuition for Hypothesis 4(ii) is as follows. Under IA, a high-B subject will receive B for sure by top ranking it if no one else top ranks B. However, if there are another one or two high-B

subjects (who may also top rank B), it can be optimal for the subject to top rank A instead. This is exactly the potential payoff that the subject can enjoy from learning about others' preferences.

We further investigate how a subject's WTP is affected by her guess of others' WTP. In our environment, investments in information acquisition under IA can be seen as strategic substitutes, as defined by Bulow, Geanakoplos and Klemperer (1985). Namely, subjects' information-acquisition investments mutually offset one another in equilibrium: A subject has a lower WTP when she expects others having a higher WTP. Intuitively, when a subject's own value is unknown, it is a dominant strategy to submit ABC; the benefit of acquiring information on one's own value is to submit BAC if school B turns out to be the best. However, the magnitude of this benefit decreases with the number of other subjects playing BAC which is positively correlated with others' WTP for information. Similar arguments apply for the incentive to acquire information about others' values. The derivations are available in Appendix A. Note that this correlation is absent under DA due to its strategy-proofness. This leads to our next hypotheses.

Hypothesis 5 (Information Acquisition as Strategic Substitutes)**.** *Under IA, subjects' WTP for OwnValue and OtherValue should be lower if they expect that others' WTP is higher. Under DA, the WTP of a subject is independent of others' WTP.*

To test Hypotheses 4 and 5, similar to our analysis of the subject-average WTP (Table 4), we specify the following Tobit model, taking into account that WTP is bounded within $[0, 15]$:

$$\begin{aligned} WTP^*_{i,t} =& \alpha_i + \beta_1 High\_B \times IA\_OtherValue_{i,t} + \beta_2 High\_B \times DA\_OtherValue_{i,t} \\ &+ \beta_3 WTP\_Guess_{i,t} + \beta_4 WTP\_Guess_{i,t} \times DA_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \\ WTP_{i,t} =& \max\{0, min\{WTP^*_{i,t}, 15\}\}, \end{aligned} \tag{1}$$

where i indexes subjects, while t indexes rounds (within each session); $WTP^*_{i,t}$ and $WTP_{i,t}$ respectively denote the unobserved latent and the observed censored WTP. Given the non-linear nature of the Tobit model, we cannot consistently estimate α_i as subject fixed effects with a short panel (ten rounds). Consequently, we use a random effects Tobit model. For the above specification, we run the analyses for all four treatments both individually and pooled.[14]

Our explanatory variables include $High\_B \times IA\_OtherValue_{i,t}$, which equals one if in round t subject i has a high value for school B under the treatment IA OtherValue, and zero otherwise. We also include $High\_B \times DA\_OtherValue_{i,t}$, which we define similarly.[15] Our theoretical model

[14]As robustness checks, we also estimate linear panel regressions with fixed effects (Table D.4) and then random effects (Table D.5) in Appendix D.

[15]For the other treatments, IA or DA OwnValue, it is impossible to define a similar variable, as subjects do not know their own value for school B when deciding whether to acquire information.

predicts that the coefficient of $High\_B \times IA\_OtherValue_{i,t}$ should be positive, whereas that of $High\_B \times DA\_OtherValue_{i,t}$ should be zero. Our empirical results support these predictions.

Another two key explanatory variables are $WTP\_Guess_{i,t}$, which is subject i's guess of her opponents' average WTP in round t, and its interaction with $DA_{i,t}$. We predict that a risk-neutral student i's own WTP and $WTP\_Guess_{i,t}$ should be independent of each other under DA and negatively correlated under IA.[16]

We note the possibility that common shocks to i in round t may affect both $WTP_{i,t}$ and $WTP\_Guess_{i,t}$. We address this potential endogeneity concern with an instrumental-variable approach and present the results in Tables D.4 and D.5 in Appendix D. Specifically, we use the realization of opponents' WTP in the previous round as an instrumental variable (IV) for $WTP\_Guess_{i,t}$. This variable is correlated with $WTP\_Guess_{i,t}$ as it provides information about how others play the game, but does not have a direct effect on $WTP_{i,t}$. Provided that the IV is valid, we fail to reject the null hypothesis that $WTP\_Guess_{i,t}$ is exogenous. Therefore, we conclude that endogeneity is not an issue for our analyses.

Finally, other controls include round (i.e., a linear time trend) and round in costly-to-free sessions. It should be emphasized that a large set of robustness checks reveals that inclusion of additional controls, such as a subject's accumulated wealth at the beginning of the round and whether a subject successfully acquired information in $t-1$, does not change our results significantly.

We present the results of our panel data analyses in column (1) of Table 5, while Table D.3 shows robustness checks with inclusion or exclusion of additional controls. These results show that the coefficient on $WTP\_Guess_{i,t}$ is always positive and significant, contrary to our theoretical predictions. Moreover, there are no significant differences between IA and DA (column 1). The positive correlation is found in every single treatment (column 2–4). Subjects lower their excess WTP over time, although this reduction is only significant in IA OwnValue. Lastly, the coefficients on our four factors ("% playing a dominated strategy with free info", curiosity, costly-to-free, and risk aversion) are similar to those in Table 4, although "% playing a dominated strategy with free info" under IA now has a larger coefficient. We summarize our results below.

Result 4 (Mechanism Effect & High-B Value)**.** *For subjects with high values for school B, controlling for their guess about others' WTP for information, their WTP for OtherValue is not significantly different from zero under DA, but is positive and significant under IA.*

By Result 4, we fail to reject Hypothesis 4(i) or (ii), indicating that the effect of having a high-

[16]With certain risk-averse subjects, the WTP is still negatively correlated with $WTP\_Guess_{i,t}$ under IA, but the correlation is weakly positive under DA for OwnValue. See Appendix B for more details.

Table 5: Determinants of WTP: Pooled and Separate Random-Effects Panel Tobit Analyses

		IA		DA	
	Pooled	OwnValue	OtherValue	OwnValue	OtherValue
	(1)	(2)	(3)	(4)	(5)
IA_OwnValue	3.48***				
	(1.26)				
IA_OtherValue	1.44				
	(1.12)				
DA_OwnValue	2.06*				
	(1.06)				
High_B × IA_OtherValue	3.16***		3.66***		
	(0.86)		(0.90)		
High_B × DA_OtherValue	-0.67				-0.63
	(1.17)				(0.96)
$WTP\_Guess_{i,t}$: Guess of Opponents' WTP in t	0.78***	0.83***	0.79***	0.90***	1.06***
	(0.14)	(0.17)	(0.15)	(0.08)	(0.21)
$WTP\_Guess_{i,t}$ × DA	0.23				
	(0.18)				
% playing a dominated strategy w/ free info (in percentage points)					
IA	0.26*	0.38*	0.13		
	(0.15)	(0.23)	(0.53)		
DA	0.08**			0.05**	0.06
	(0.03)			(0.03)	(0.07)
Curiosity	0.39***	0.32**	0.50**	0.35***	0.44***
	(0.06)	(0.16)	(0.22)	(0.12)	(0.14)
Costly-to-free	1.23*	2.02*	2.71***	-0.23	-0.41
	(0.65)	(1.12)	(0.99)	(1.15)	(1.88)
Risk Aversion	-0.35	-1.63***	-0.41	-0.37	0.31
	(0.21)	(0.53)	(0.31)	(0.32)	(0.24)
Round	-0.04	-0.11***	0.15	0.02	-0.24
	(0.07)	(0.03)	(0.25)	(0.05)	(0.17)
Round × Costly-to-free	-0.10	-0.20***	-0.19	-0.06	0.11
	(0.09)	(0.07)	(0.27)	(0.06)	(0.18)
Other demographical controls	Yes	Yes	Yes	Yes	Yes
# of observations	2169	567	513	576	513
# of subjects	241	63	57	64	57

Notes: Estimates are from random effects panel Tobit models for each treatment separately and pooled, including only consistent subjects in the Holt-Laury lottery game. The sample includes 9 rounds of costly information acquisition for every subject, excluding the first round. Column (1) repeats column (2) in Table D.3. All specifications include these additional controls: dummy for female, dummy for graduate student, dummy for black, dummy for Asian, dummy for Hispanic, age, ACT score, SAT score, dummy for ACT score missing, dummy for SAT score missing, dummy for degree missing, dummy for age missing, dummy for ethnicity missing, and dummy for gender missing. Standard errors clustered at session level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B value on WTP for OtherValue is largely consistent with our theoretical predictions under both IA and DA. By contrast, we obtain the following result regarding conformity.

Result 5 (Conformity)**.** *Subjects who expect their opponents to have a higher WTP increase their own WTP for OwnValue and OtherValue; there is no significant difference between IA and DA.*

By Result 5, we reject Hypothesis 5. This result indicates that subjects are willing to pay more to know their own and others' preferences when they expect their opponents have high WTPs, a phenomenon we call *conformity*. This could be due to a consensus effect according to which people think others do what they themselves do. It could also be a competitive effect whereby subjects believe they need to be informed to compete with others who are informed as well. For brevity, we use the term conformity but remain agnostic to the causes of this phenomenon.

5.2 Decomposition of a Subject's WTP

In this section, we investigate possible reasons that subjects over-invest in information acquisition. Specifically, we decompose our observed WTP treatment-by-treatment according to the following factors identified in our panel analysis: order effect, learning over rounds, "% playing a dominated strategy with free info", conformity, curiosity, and risk aversion.

To perform our decomposition, we first estimate the Tobit model, as in equation system (1), for each separate treatment (columns 2–5 in Table 5). Doing so allows each factor to have a different effect in a given treatment, as the coefficients for some of our key variables change across treatments. Based on these estimated coefficients, Table 6 presents the decomposition of subject WTP for information. Overall, this analysis shows that our six factors can explain the majority of the observed WTP.[17] We discuss each factor below.

(i) Order Effect. The costly-to-free order is associated with an average of 1.23 points extra WTP in every round among all treatments (Table 5, column 1), but that this effect is not present in the DA treatments (Table 5, columns 4 and 5). Moreover, the order also affects learning over rounds based on the coefficients on "Round" and "Round $\times$ Costly-to-free": in costly-to-free sessions, learning over rounds reduces WTP faster. Indeed, by round 10, WTP in costly-to-free sessions is reduced by 1.12 points relative to round 2, while this reduction is only 0.32 in free-to-costly sessions.

To quantify the order effect, we consider the counterfactual of replacing costly-to-free by free-to-costly, i.e., setting both "Costly-to-free" and "Round $\times$ Costly-to-free" to zero. We then measure the order effect as the difference between the model prediction based on the true variable values and the prediction under the counterfactual. Both predictions are censored to guarantee that the predicted WTP falls between 0 and 15. Table 6 shows that the presence of order effect contributes to WTP by -0.21 to 1.18 points across treatments.

(ii) Learning over rounds. To assess learning over rounds, we consider the counterfactual of replacing a subject's behavior in rounds 2–9 with her behavior in round 10, as round 1 is omitted from our regression. Using the same censoring as above, we find that the estimated effect of

[17] As a robustness check, decompositions based on the pooled regression (column 1 in Table 5) are presented in Table D.6 in Appendix D, which show similar results.

Table 6: Decomposition of Subject WTP for Information

	IA OwnValue (1)	IA OtherValue (2)	DA OwnValue (3)	DA OtherValue (4)
WTP: data	**6.44**	**4.32**	**4.17**	**1.84**
	(4.87)	(4.68)	(4.30)	(2.86)
Model prediction[a]	6.35	4.19	4.13	1.73
	(3.28)	(2.94)	(2.90)	(2.10)
(i) Order effect[b]	1.18	1.02	0.01	-0.21
	(0.53)	(0.65)	(0.23)	(0.17)
(ii) Learning over rounds[b]	0.64	-0.09	0.06	0.31
	(0.59)	(0.27)	(0.13)	(0.36)
(iii) Conformity[b]	3.91	2.21	2.60	1.31
	(1.93)	(1.71)	(2.05)	(1.69)
(iv) % playing a dominated strategy w/ free info[b]	0.26	0.03	0.30	0.24
	(0.77)	(0.15)	(0.52)	(0.60)
(v) Curiosity[b]	1.35	1.38	0.95	0.52
	(1.40)	(1.70)	(1.30)	(1.11)
(vi) Risk aversion[b]	-1.62	-0.32	-0.44	0.27
	(1.45)	(0.38)	(0.44)	(0.31)
Total Explained by factors (i)-(vi)[c]	**5.23**	**3.49**	**3.22**	**1.62**
	(2.99)	(2.67)	(2.63)	(2.08)
Residual WTP[d]	**1.20**	**0.83**	**0.94**	**0.21**
	(3.60)	(3.78)	(2.99)	(2.12)
Theoretical prediction[e]	**[5.2, 8]**	**[0, 0.24]**	**0.67**	**0.00**
# of observations	567	513	576	513
# of subjects	63	57	64	57

Notes: Decompositions are based on the random effects Tobit model for each treatment (columns 2–5 in Table 5). The table reports the sample average, while standard deviations are in parentheses.

a. "Model prediction" is the predicted value of WTP based on the corresponding estimated model, assuming that unobserved error terms are equal to zero. The predicted values are censored to be in $[0, 15]$.

b. The WTP explained by the corresponding factor is the difference between the model prediction with and without that factor. The former is predicted from the current values of all variables; the latter is calculated by setting the relevant variable value to zero (for "Order effect," "Conformity," "% playing a dominated strategy w/ free info," or "Curiosity") or setting the relevant variable to the counterfactual value (for "Risk aversion," the risk aversion measure is set to the risk-neutral value; for "Learning over round," "Round" is set to be the last round, "Round" $= 10$).

c. "Total Explained by factors (i)-(vi)" is the total WTP explained by the six factors above. Note that it is not the sum of the explained WTP of the six factors because of the censoring at 0 and 15.

d. "Residual WTP" is the difference between the observed WTP and the total WTP explained by the six factors.

e. The theoretical predictions are for risk neutral subjects.

learning, or the difference between the prediction with the true variable values and the prediction under the counterfactual, accounts for between -0.09 to 0.64 points of WTP.

(iii) Conformity. Conformity measures the extent to which subjects positively respond to their beliefs about others' WTP, WTP_Guess. We find that increasing WTP_Guess by one point raises a subject's WTP by 0.78 points under IA and 1.01 points under DA (Table 5, column 1).

Although our theory predicts a negative correlation between a subject's own WTP and WTP_Guess, out counterfactual considers a zero correlation. That is, in the counterfactual, WTP_Guess has no effect on WTP. Conformity can explain 1.31 to 3.91 points of the observed WTP, or 51% to 71%, indicating that it is the single most important factor in explaining the observed WTP.

(iv) % playing a dominated strategy with free info. This measure is the proportion of time that a subject plays a dominated strategy in rounds with free information. The results in Table 5 show that it increases a subject's WTP.

To quantify its contribution, we consider the counterfactual in which no one plays a dominated strategy (i.e., setting the variable to zero). We then calculate the difference between the model prediction with the true variable values and the prediction under the counterfactual. The results in Table 6 show that the effect is between 0.03 and 0.30 points.

(v) Curiosity. The regression in column (1) of Table 5 shows that a one-point increase in WTP for non-instrumental information is associated with 0.39 additional points of WTP in each round. We consider the counterfactual where WTP for information in the school choice game is not associated with curiosity by setting the coefficient on curiosity to zero. We find that curiosity explains 0.52 to 1.38 points of the observed WTP, or 21% to 32%, indicating that this is the second most important factor in explaining the observed WTP.

(vi) Risk aversion. To measure risk aversion, we use a subject's switching point in the Holt-Laury lottery choice game. In general, our results show that being more risk averse is correlated with a lower WTP, which is consistent with our theoretical predictions, albeit insignificantly so (Table 5, column 1). However, this correlation is heterogeneous across treatments, and becomes positive in the DA OtherValue treatment.

We consider the counterfactual where every subject is risk neutral (i.e., switching at the 5th choice in the Holt-Laury game), which requires us to change about 78% of our subjects from risk averse to risk neutral. Doing so, we find that risk aversion decreases WTP by 0.32 to 1.62 points, with the exception that it increases WTP in the DA OtherValue treatment.

Together, these findings can be summarized in the following result.

Result 6 (Decomposing WTP)**.** *The six factors combined explain 77–88% of the observed WTP for information; conformity alone explains 51–71% of the WTP, while curiosity explains 21–32%.*

Overall, after accounting for the WTP explained by the six factors, the remaining WTP is similar to the level predicted by our theory for our two DA treatments. However, it is below the theoretical prediction level for the IA OwnValue treatment, and slightly above the theoretical prediction for the IA OtherValue.

5.3 Heterogeneity: Under-Acquisition of Information

While the subjects on average over-acquire information relative to the theoretical predictions, a small fraction of them never acquire information. We define that a subject has *zero demand* for information if her WTP is zero in every round. We are interested in how these subjects use freely provided information, which may have implications for policy intervention: a strong case for information provision can be made if they use freely provided information as efficiently as others.

Let $ZeroD_i$ equal to 1 if subject i has zero demand for information and 0 otherwise. Overall, 44 subjects (15% of our sample) have $ZeroD_i = 1$.[18] As zero demand in DA OtherValue coincides with the theoretical predictions, we exclude the treatment in subsequent analysis.

First, we investigate the characteristics of those with zero demand in a linear probability model (Table D.8 in Appendix D) and we find that curiosity is negatively and significantly correlated with zero demand, whereas none of the demographics is robustly correlated with it.

Second, we examine whether subjects with zero demand use free information less efficiently than others, taking advantage of a unique design feature: every subject plays the same game for 10 rounds with free information provision.

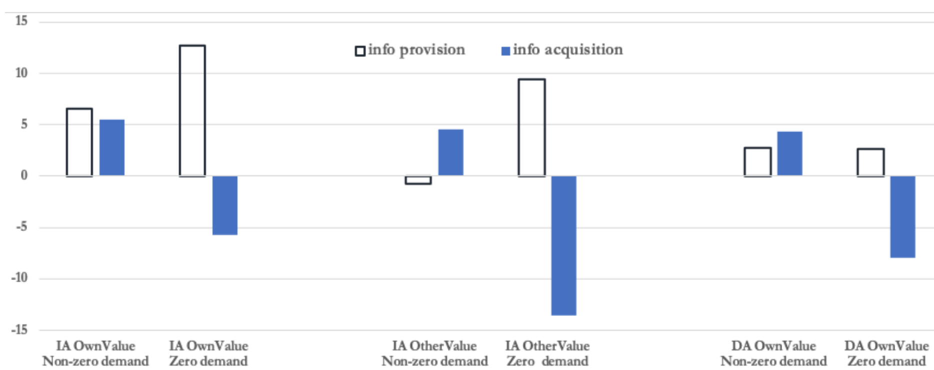

Figure 3: Effects of Information Provision and Costly Acquisition on Revenue by Subject Type

Notes: Revenue is calculated relative to the case in which the information in question is not provided or not possible to be acquired. The actual costs paid for information acquisition are not considered here. A subject has "zero demand" for information if her WTP is zero in every round.

For each subject type, zero-demand versus others, Figure 3 shows the effect of information provision or costly information acquisition on subjects' revenue from the school choice game in each treatment (without considering information costs). Specifically, the effect is the difference between a subject's revenue from information provision (white bar) or costly information acquisition (blue bar) and that from the corresponding no-information plays.

[18] $ZeroD_i = 1$ for 8% of the subjects in IA OwnValue, 10% in IA OtherValue, 15% in DA OwnValue, and 28% in DA OtherValue.

As Figure 3 shows, zero-demand subjects use freely provided information as effectively as others (two-sided $p > 0.43$ when the treatments are pooled or separated). However, when information is costly, zero-demand subjects obtain significantly lower revenue than others (treatments pooled: two-sided $p < 0.005$; individual treatment: two-sided $p < 0.08$ in all cases except IA OwnValue). These results are robust even after we account for information acquisition costs incurred by subjects with positive demand (Figure D.1), as information costs are on average low (Table D.7).

While these findings rely on a small subsample, they suggest that free information provision benefits zero-demand subjects, as they use information as effectively as others. Even a small cost of information acquisition can make such subjects worse off due to their under-acquisition.

5.4 Welfare Analysis: Payoffs and Allocative Efficiency

Our final set of analyses examine the welfare effects of both information provision by an educational authority and information acquisition by subjects. We use two welfare measures: the payoffs that subjects receive in the experiment and the efficiency of the allocation outcome. An allocation is deemed efficient if a subject, who values school B at 110, is matched with school B whenever at least one such subject exists.

Table 7: Effects of Information Acquisition & Provision in the Experiment

	Information Provision				Information Acquisition (Observed)			
	Net payoff gain		Efficiency gain (%)		Net payoff gain	Efficiency gain (%)	Prob of info acquired	Costs paid
	Theoretical (1)	Observed (2)	Theoretical (3)	Observed (4)	(5)	(6)	(7)	(8)
IA OwnValue	9.6	8.16***	32	24***	2.29**	14***	0.44	2.25
		(0.64)		(1.90)	(0.70)	(2.10)		
IA OtherValue	0	-0.01	0	2	0.10	4	0.28	1.29
		(1.21)		(3.02)	(0.97)	(3.05)		
DA OwnValue	5.24	4.26**	19	13**	-0.28	3	0.3	1.35
		(1.60)		(4.69)	(0.72)	(2.06)		
DA OtherValue	0	0.20	0	1	-0.98	0	0.14	0.48
		(1.46)		(2.87)	(1.07)	(2.05)		

Notes: Detailed estimates are in Tables E.1 and E.2. Given a treatment, the welfare effect measures the difference between the payoff (per subject, per round) with free information provision (or costly information acquisition) and the payoff without the information in question, net of the costs of information acquisition paid in the experiment. The effect on allocation efficiency, reported in percentage points, is similarly calculated at the game level; each game outcome is either efficient or inefficient. The theoretical effects are derived for risk-neutral subjects. Standard errors allowing arbitrary correlation within a session are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, for testing the null of no effect.

When studying information provision, we consider the three standard information structures: (i) *ex ante*, where everyone knows the distribution of school B values but not its realization, (ii) *interim*, where everyone knows the distribution of school B values and her own value, but not others' values, and (iii) *ex post*, where everyone's school B value is common knowledge. An information structure is changed from *ex ante* to *interim* with free information in the OwnValue treatments, and from *interim* to *ex post* in the OtherValue ones. The theoretical effects of information provision for risk-neutral subjects are summarized in Table 7, leading to the following hypothesis:

Hypothesis 6 (Effects of Information Provision)**.** *"Providing OwnValue" (i.e., transforming ex ante into interim) increases subject payoffs and allocation efficiency under either mechanism, but "providing OtherValue" (i.e., transforming interim to ex post) has no effect on subject payoffs or allocation efficiency under IA or DA.*

Given our experimental design, we can perform within-subject tests of the effects of information provision for each treatment. For instance, in IA OwnValue, we calculate each subject's payoff difference between *ex ante* and *interim*, because she plays the game knowing only the distribution (*ex ante*) and the game knowing her own school B value (*interim*) in the free information rounds within the same treatment. We then test if this difference is zero.

Result 7 (Effects of Information Provision)**.** *(i) "Providing OwnValue" increases subject payoffs and the fraction of efficient allocations under both IA and DA; (ii) "providing OtherValue" has no effect on subject payoffs or allocation efficiency under IA or DA.*

Support: Columns (2) and (4) in Table 7 show the results. Providing information on OwnValue leads to an extra payoff of 8.16 under IA and 4.26 under DA, and increases the fraction of efficient allocation by 24 percentage points under IA and 19 percentage points under DA, all significant at the 5% level. Under either mechanism, providing information on OtherValue results in effects that are close to zero and statistically insignificant. ∎

Regarding the effects of information acquisition with low costs, we expect outcomes to fall between no information and free information provision. This is because not everyone succeeds in information acquisition (column 7, Table 7). Our experiment indeed adopts a low-cost technology, as a subject on average pays half of her WTP if and only if information is successfully acquired.[19] The actual costs paid are between 0.48–2.25 (column 8). This leads to our final hypothesis.

Hypothesis 7 (Effects of Costly Information Acquisition)**.** *"Acquiring OwnValue" increases subject payoffs and the fraction of efficient allocations under either mechanism, but "acquiring OtherValue" has no effect on subject payoffs or allocation efficiency for IA or DA.*

Result 8 (Effects of Information Acquisition)**.** *(i) "Acquiring OwnValue" improves both subject payoffs and allocation efficiency for IA but not for DA; (ii) "Acquiring OtherValue" does not affect either subject payoffs or allocation efficiency for IA or DA.*

[19]Given the experimental design, when one's WTP is w, the expected cost of information acquisition is $w^2/30$.

Support: Columns (5) and (6) in Table 7 report the results. "Acquiring OwnValue" under IA increases subject payoffs by 2.29 and the fraction of efficient allocations by 14 percentage points, both significant at the 5% level. "Acquiring OwnValue" under DA has insignificant effects on either welfare measures, so does "Acquiring OtherValue" under IA and DA. ■

Results 7 and 8 together show that costly information acquisition can only achieve a small fraction of the benefits of information provision, even when the information cost is low. We may expect that subject payoffs can be even lower if the information acquisition is more costly.

This motives us to consider broader information provision policies, e.g., providing both OwnValue and OtherValue. Indeed, the analysis in Appendix E.3 shows that such a policy under IA or DA can achieve a welfare level close to the efficient outcome in *interim*, or equivalently *ex post*. A key component of this welfare gain is that providing OtherValue can reduce wasteful investments in information acquisition, especially when students may invest up to their WTP. Importantly, this waste reduction extends to DA under which students should have a zero WTP for such information.

Lastly, we investigate how OtherValue, when being exogenously provided or endogenously acquired, affects the rate of dominant strategy play in a strategy-proof mechanism relative to *interim*. Recall that knowing OtherValue in our setting helps subjects better assess admission chances at all schools. Under DA in *interim*, admission chances conditional on truth-telling are always non-degenerate, or in $(0, 1)$, because of the post-application lottery, and therefore truth-telling is the unique equilibrium (Fack, Grenet and He 2019). *Ex post*, 84% of the subjects across all possible type compositions in the game have truth-telling as the unique equilibrium strategy.[20]

Result 9 (Effects of Information about OtherValue on Truth-telling in DA)**.** *When OwnValue is private information, the proportion of truth-telling subjects under DA remains constant whether OtherValue is exogenously provided or endogenously acquired.*

Support: This result can be obtained from within-subject analyses of the DA OtherValue treatment. The fraction of truth-telling subjects is 91% in *interim* and 92% when OtherValue is freely provided or endogenously acquired (although they can choose not to acquire it). Furthermore, in *interim* in the DA OwnValue treatment when OwnValue is freely provided, the truth-telling rate is 92%. There are no significant differences between any pair of these statistics. Appendix D.4 provides additional analyses. ■

[20] *Ex post*, truth-telling is not the unique equilibrium strategy for two types of subjects: those with a low B value while her two opponents have a high B value and those with a high B value while her two opponents have a low B value. Truth-telling being the unique equilibrium strategy for all or most of the subjects may also explain the high rate of truth-telling in our data relative to other studies that often have multiple equilibria under DA.

Result 9 does not contradict the findings in Pais and Pintér (2008). In their setting, the least informative condition, called "zero" information, has OwnValue as private information but lacks a common prior and information on schools' priorities. Other information conditions provide more information that can help subjects form a better assessment of admission chances: subjects' own school priorities ("low" information), all subjects' school priorities ("partial" information), and preferences and priorities of all subjects ("full" information). They find that truth-telling under DA decreases from zero to any other information condition whereas none of the other pairwise comparisons is significant. This finding can be explained by the existence of multiple equilibria under all information conditions except zero. Specifically, certain schools will be out of her reach if her priorities at those schools are too low; with this information, she can rank arbitrarily these schools in her ROL without any payoff loss.[21] A school rarely, if ever, becomes out of reach for a student when schools rank students solely by a post-application lottery as in our setting.

6 Conclusion

We present experimental evidence that the two most popular school choice mechanisms, DA and IA, provide heterogeneous degrees of incentives for students to acquire information on their own and others' preferences. Information on own preferences is about one's match values at schools, while that on others' preferences helps her better assess her admission chances.

We first find is that better information about a subject's own preferences improves both student payoffs and the student-school match efficiency, in line with recent calls for better information provision on school quality. In practice, the information about a student's own preferences can be provided through accessible presentation materials on school offerings and performance (Hastings and Weinstein 2008), and by knowledgeable guidance counselors and teachers (Sattin-Bajaj 2014).

We also show that information provision on others' preferences, or information about admission chances, reduces wasteful investments. In practice, information provision about admission chances can be implemented through publicizing application behaviors, such as publishing data on student application statistics in past years (Chen, Jiang and Kesten forthcoming), or publishing applicants' actions and allowing students to revise their own applications upon observing others' actions. The latter information policy is already adopted in the school choice context in Amsterdam (De Haan, Gautier, Oosterbeek and Van der Klaauw 2015) and Wake County, North Carolina (Dur, Hammond and Morrill 2018), as well as in the college admissions context in Inner Mongolia

[21] This pattern is documented in the Australian college admissions by Artemov, Che and He (2017) who also provide a theoretical investigation.

through a dynamically updated web interface (Gong and Liang 2017).

Policymakers should use caution, however, when publishing information on others' actions. Past experiments demonstrate that, when others' strategies are not optimal, participants who do not understand the properties of the matching mechanism might copy those suboptimal strategies (Guillen and Hakimov 2017), resulting in a potentially negative effect of information provision. In this case, policymakers may consider explaining the properties of the mechanism to guide participants' behavior (Guillen and Hakimov 2018).

Lastly, a substantial fraction of our subjects have information preferences, such as curiosity and zero demand for information. This implies that theories of information acquisition in market design may improve its behavioral predictions by incorporating such preferences.

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Online Appendices for

Information Acquisition and Provision in School Choice

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Appendix A Model setup and equilibrium analysis with risk-neutral students

A.1 The Setup

In addition to the model setup in the main text, student preferences are strict: For any pair of distinct schools s and t in S, $v_{i,s} \neq v_{i,t}$ for all i. We therefore define strict ordinal preferences P on S such that sP_it if and only if $v_{i,s} > v_{i,t}$. We also augment the set of all possible strict ordinal preferences $\mathcal{P}$ with a "null preference" $P^{\phi} \equiv \emptyset$ denoting that one has no information on her ordinal preference, expressed as $\bar{\mathcal{P}} = \mathcal{P} \cup \emptyset$. The distribution of V conditional on P is denoted by $F(V|P)$, while the probability mass function of P implied by F is $G(P|F)$ ($\mathcal{P}$ is finite). We impose a full-support assumption on $G(P|F)$, i.e., $G(P|F) > 0, \forall P \in \mathcal{P}$, indicating that every strict ordinal preference ranking is possible given the distribution of cardinal preferences. Necessarily, $G(P^{\phi}|F) = 0$.

In our model, the value of the outside option and the distribution of preferences, $F(V)$ and thus $G(P|F)$, are always common knowledge. However, in contrast to previous models of school choice, we introduce an information-acquisition stage for each i to learn her own preferences (P_i and/or V_i) or others' preferences (V_{-i}) before entering the mechanism. Because of the independent-private-value nature, learning about others' preferences is only for the purpose of gaming or competing with other students. The process and technology for information acquisition for own (resp. others') values are depicted in Figure A.1 (resp. A.2), both reproduced from Chen and He (2018).

To acquire information, student i may pay δ to acquire a signal of V_{-i}, $\omega_{i,3} \in \bar{\mathcal{V}}^{(|I|-1)}$. With probability $d(\delta)$, she learns perfectly, $\omega_{3,i} = V_{-i}$; with probability $1 - d(\delta)$, $\omega_{3,i} = V_{-i}^{\phi}$, i.e., she learns nothing.

The technology has the following properties: $d(0) = 0$, $\lim_{\delta \to \infty} d(\delta) = 1$, $d' > 0$, $d'' < 0$, and $d'(0) = \infty$. The cost for information acquisition is $e(\delta)$ such that $e(0) = 0$, $e', e'' > 0$ and $e'(0) < \infty$. Similarly, we restrict our attention to $\delta \in [0, \bar{\delta}]$, where $e(\bar{\delta}) = \overline{v}$.

Information acquisition is again covert. We focus on a symmetric Bayesian Nash equilibrium, $(\delta^*(V), \bar{\sigma}^*(\omega_3, V))$, where:

(i) A (possibly mixed) strategy $\bar{\sigma}^*(\omega_3, V) : \bar{\mathcal{V}}^{(|I|-1)} \times \mathcal{V} \to \Delta(\mathcal{P})$, such that

$$\bar{\sigma}^*(\omega_{3,i}, V_i) \in \arg\max_{\bar{\sigma}} \left\{ \int \int u(V_i, \bar{\sigma}, \bar{\sigma}^*(\omega_{3,-i}, V_{-i})) \, dF(V_{-i}|\omega_{3,i}) \, dK\left(\omega_{3,-i}|\delta^*_{-i}\right) \right\}.$$

That is, given one's own signal $\omega_{3,i}$, everyone plays a best response, recognizing that everyone has paid δ^* to acquire information (denoted as δ^*_{-i}). We further define the value function given $\left(\omega_{3,i}, \delta^*_{-i}\right)$ and V_i as:

$$\Phi\left(V_i, \omega_{3,i}, \delta^*_{-i}\right) = \max_{\bar{\sigma}} \left\{ \int \int u(V_i, \bar{\sigma}, \bar{\sigma}^*(\omega_{3,-i}, V_{-i})) \, dF(V_{-i}|\omega_{3,i}) \, dK\left(\omega_{3,-i}|\delta^*_{-i}\right) \right\}.$$

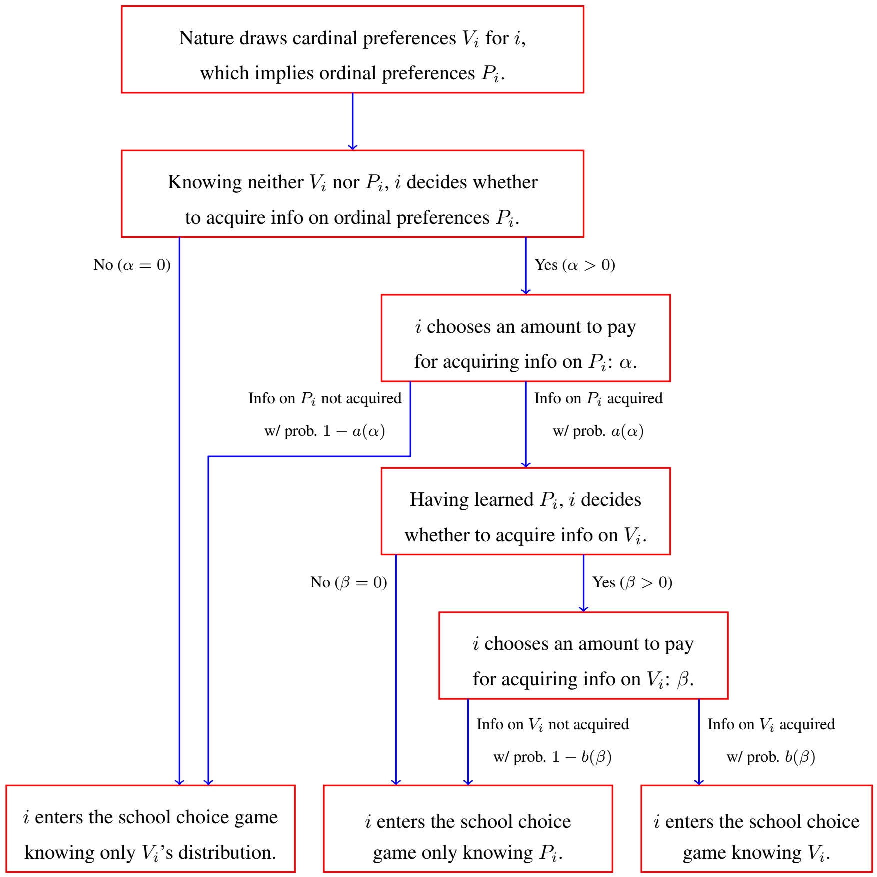

Figure A.1: Acquiring Information on One's Own Preferences.

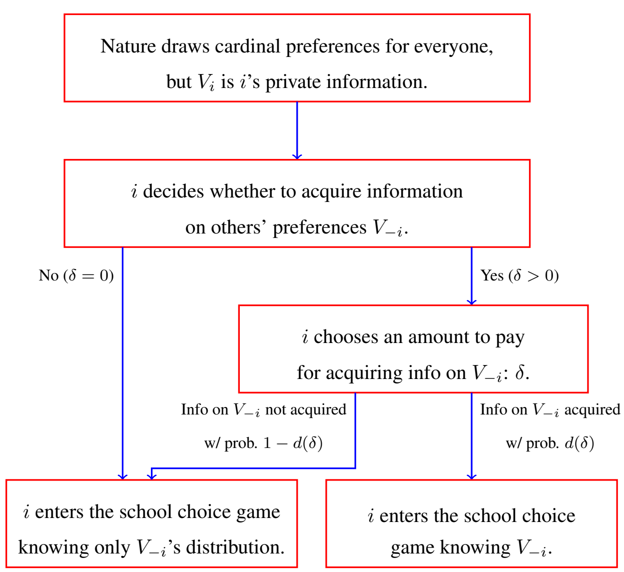

Figure A.2: Acquiring Information on Others' Preferences.

(ii) Acquisition of information on others' preferences $\delta^*(V) : \bar{\mathcal{V}} \to [0, \bar{\delta}], \forall V$:

$$\delta^*(V_i) \in \arg\max_{\delta} \left\{ d(\delta) \int \Phi\left(V_i, V_{-i}, \delta^*_{-i}\right) dF(V_{-i}) + (1 - d(\delta)) \Phi\left(V_i, V^{\phi}_{-i}, \delta^*_{-i}\right) - e(\delta) \right\}.$$

Here, $\delta^*(V_i)$ is the optimal information acquisition strategy.

A.2 Equilibrium analysis with risk neutral students

Given the payoff table used in the experiment, Table 1 in section 4, this appendix derives the equilibrium strategies and payoffs under the assumption that every student is risk neutral. Note that we will be using the dollar amount rather than points in our derivations. We also vary information structure and derive the incentive to acquire information. The results on risk-averse students are presented in Appendix B. Throughout, students do not know the realization of tie breakers when playing the game. We consider the following 5 scenarios where the information structure differs:

(1) Complete information about preferences (*ex post*): Everyone knows her own and others' realized preferences;

(2) Incomplete information about preferences (*interim*): Everyone knows her own realized preferences but only the distribution of others' preferences;

(3) Unknown preferences (*ex ante*): Everyone only knows the distribution of her own and others' preferences;

(4) Unknown preferences (Scenario 3) with acquisition of information about one's own preferences;

(5) Incomplete information (Scenario 2) with acquisition of information about others' preferences.

The literature on school choice, or on matching in general, focuses on the first three scenarios. By introducing scenarios (4) and (5), we extend the literature by endogenizing the acquisition of information about one's own or on others' preferences.

In the following, we calculate the expected payoff that is evaluated at *ex ante* (i.e., from the time point before the realization of the preferences).

A.3 Scenario (1): Complete Information about Preferences (*ex post*)

IA: Table A.1 iterates through each realization of preference profiles and compute the symmetric equilibrium strategies and payoffs under IA.

Ex ante, before the realization of the preferences, given that they know they will play the game with complete information under IA, the expected payoff of each student is:

$$\frac{4}{5}\left(\frac{11}{30}\frac{16}{25} + \frac{1}{2}\frac{8}{25} + \frac{1}{25}\right) + \frac{1}{5}\left(\frac{11}{10}\frac{16}{25} + \frac{11}{20}\frac{8}{25} + \left(\frac{7}{10}\right)\frac{1}{25}\right) = \frac{4}{5}\frac{326}{750} + \frac{1}{5}\frac{681}{750} = \frac{397}{750}.$$

Table A.1: Symmetric equilibrium under IA given each realization of preference profiles

Realization of Preference	Probability Realized	Action given realized type (1, 0.1, 0)	Action given realized type (1, 1.1, 0)	Payoff given realized type (1, 0.1, 0)	Payoff given realized type (1, 1.1, 0)
(1, 0.1, 0) (1, 0.1, 0) (1, 0.1, 0)	64/125	(a, b, c)	-	11/30	-
(1, 1.1, 0) (1, 0.1, 0) (1, 0.1, 0)	48/125	(a, b, c)	(b, a, c)	1/2	11/10
(1, 1.1, 0) (1, 1.1, 0) (1, 0.1, 0)	12/125	(a, b, c)	(b, a, c)	1	11/20
(1, 1.1, 0) (1, 1.1, 0) (1, 1.1, 0)	1/125	-	(a, b, c) w/ prob. 3/7[a] (b, a, c) w/ prob. 4/7[a]	-	7/10

a. We may allow one student to play (a,b,c) and the other two to play (b,a,c), which is a pure-strategy Nash equilibrium. If everyone has the same probability to play (a,b,c), the expected payoff of everyone is also 7/10.

DA: Before looking at equilibrium, we use Table A.2 to clarify the assignment probabilities given students' actions. Note that we always use DA with single tie-breaking.

Given any realization of the preferences, Table A.3 presents the equilibrium strategies and payoffs under DA.

Ex ante, before the realization of the preferences, given that they know they will play the game with complete information under DA, the expected payoff to each student is:

$$\frac{4}{5}\left(\frac{11}{30}\frac{16}{25}+\frac{31}{60}\frac{8}{25}+\frac{2}{3}\frac{1}{25}\right)+\frac{1}{5}\left(\frac{22}{30}*\frac{16}{25}+\frac{43}{60}\frac{8}{25}+\left(\frac{21}{30}\right)\frac{1}{25}\right)=\frac{365}{750}.$$

A.4 Scenario (2): Incomplete Information about Preferences (*interim*)

IA: When one's own preferences are private information and the distribution of preferences is common knowledge, there is a unique symmetric equilibrium under IA:

$$\sigma_{IA}^{(2)}\left((1,1.1,0)\right)=(b,a,c)\,;\sigma_{IA}^{(2)}\left((1,0.1,0)\right)=(a,b,c)\,.$$

For any given student, there are three possibilities of opponents' types:

Types	Probability	Others' Action Profile
(1, 0.1, 0) (1, 0.1, 0)	16/25	(a, b, c) (a, b, c)
(1, 1.1, 0) (1, 0.1, 0)	8/25	(b, a, c) (a, b, c)
(1, 1.1, 0) (1, 1.1, 0)	1/25	(b, a, c) (b, a, c)

For a type-$(1, 0.1, 0)$ student, it is a dominant strategy to play (a, b, c). Conditional on her type,

Table A.2: Assignment probability under DA given each strategy profile

Submitted List	Probability of Being Assigned to Each School if Playing (a, b, c)			Playing (b, a, c)		
	a	b	c	a	b	c
(a, b, c) (a, b, c) (a, b, c)	$1/3$	$1/3$	$1/3$	-	-	-
(b, a, c) (a, b, c) (a, b, c)	$1/2$	$1/6$	$1/3$	0	$2/3$	$1/3$
(b, a, c) (b, a, c) (a, b, c)	$2/3$	0	$1/3$	$1/6$	$1/2$	$1/3$
(b, a, c) (b, a, c) (b, a, c)	-	-	-	$1/3$	$1/3$	$1/3$

Table A.3: Symmetric equilibrium under DA given each realization of preference profiles

Realization of Preference	Probability Realized	Action given realized type (1, 0.1, 0)	Action given realized type (1, 1.1, 0)	Payoff given realized type (1, 0.1, 0)	Payoff given realized type (1, 1.1, 0)
(1, 0.1, 0) (1, 0.1, 0) (1, 0.1, 0)	64/125	(a, b, c)	-	11/30	-
(1, 1.1, 0) (1, 0.1, 0) (1, 0.1, 0)	48/125	(a, b, c)	(b, a, c)	$\frac{1}{2}+\frac{1}{60}$ $= 31/60$	$\frac{2}{3}\frac{11}{10}$ $= 22/30$
(1, 1.1, 0) (1, 1.1, 0) (1, 0.1, 0)	12/125	(a, b, c)	(b, a, c)	2/3	$\frac{11}{20}+\frac{1}{6}$ $= 43/60$
(1, 1.1, 0) (1, 1.1, 0) (1, 1.1, 0)	1/125	-	(b, a, c)	-	21/30

her equilibrium payoff is:

$$\frac{16}{25}\left(\frac{1}{3}\left(1+\frac{1}{10}+0\right)\right)+\frac{8}{25}\frac{1}{2}+\frac{1}{25}=\frac{326}{750}.$$

If a type-$(1, 0.1, 0)$ student deviates to (b, a, c), she obtains:

$$\frac{16}{25}\left(\frac{1}{10}\right)+\frac{8}{25}\left(\frac{1}{2}\left(\frac{1}{10}+0\right)\right)+\frac{1}{25}\left(\frac{11}{30}\right)=\frac{71}{750}.$$

For a type-$(1, 1.1, 0)$ student, given others follow $\sigma_{BM}^{(2)}$, playing (b, a, c) results in a payoff of:

$$\frac{16}{25}\frac{11}{10} + \frac{8}{25}\left(\frac{1}{2}\left(\frac{11}{10} + 0\right)\right) + \frac{1}{25}\left(\frac{1}{3}\left(\frac{11}{10} + 1 + 0\right)\right) = \frac{681}{750}.$$

If a type-$(1, 1.1, 0)$ student deviates to (a, b, c), she obtains:

$$\frac{16}{25}\left(\frac{1}{3}\left(\frac{11}{10} + 1 + 0\right)\right) + \frac{8}{25}\left(\frac{1}{2}(1 + 0)\right) + \frac{1}{25}(1) = \frac{486}{750}.$$

It is therefore not a profitable deviation. Furthermore, she has no incentive to deviate to other rankings such as (c, a, b) or (c, b, a).

Before the realization of their own preferences while knowing that they will play the game under DA with incomplete information, the expected payoff to every student is:

$$\frac{326}{750}\frac{4}{5} + \frac{681}{750}\frac{1}{5} = \frac{397}{750}.$$

Remark A.1. *Note that the two scenarios, (1) and (2), result in the same payoffs under IA.*

Remark A.2. *In neither scenario is a type-*$(1, 0.1, 0)$ *student ever matched with school* B *as long as there is at least one type-*$(1, 1.1, 0)$ *student.*

DA: When one's own preferences are private information and the distribution of preferences is common knowledge, there is a unique equilibrium under DA:

$$\sigma_{DA}^{(2)}((1, 1.1, 0)) = (b, a, c)\,; \sigma_{DA}^{(2)}((1, 0.1, 0)) = (a, b, c)\,.$$

For any given student, there are three possibilities of opponents' types:

	Types	Probability	Others' Action Profile
1	(1, 0.1, 0) (1, 0.1, 0)	16/25	(a,b, c) (a, b, c)
2	(1, 1.1, 0) (1, 0.1, 0)	8/25	(b, a,c) (a, b, c)
3	(1, 1.1, 0) (1, 1.1, 0)	1/25	(b, a,c) (b, a, c)

For a type-$(1, 0.1, 0)$ student, it is a dominant strategy to play (a, b, c). Conditional on her type, her equilibrium payoff is:

$$\frac{16}{25}\left(\frac{1}{3}\left(1 + \frac{1}{10} + 0\right)\right) + \frac{8}{25}\left(\frac{1}{2} + \frac{1}{60} + 0\right) + \frac{1}{25}\left(\frac{2}{3} + 0\right) = \frac{320}{750}.$$

If a type-$(1, 0.1, 0)$ student deviates to (b, a, c), she obtains:

$$\frac{16}{25}\left(\frac{2}{30} + 0\right) + \frac{8}{25}\left(\frac{1}{20} + \frac{1}{6} + 0\right) + \frac{1}{25}\left(\frac{1}{3}\left(1 + \frac{1}{10} + 0\right)\right) = \frac{95}{750}.$$

For a type-$(1, 1.1, 0)$ student, given others follow $\sigma_{DA}^{(2)}$, playing (b, a, c) results in a payoff of:

$$\frac{16}{25}\left(\frac{2}{3}\frac{11}{10}\right)+\frac{8}{25}\left(\frac{1}{2}\frac{11}{10}+\frac{1}{6}\right)+\frac{1}{25}\left(\frac{1}{3}\left(\frac{11}{10}+1+0\right)\right)=\frac{545}{750}.$$

If a type-$(1, 1.1, 0)$ student deviates to (a, b, c), she obtains:

$$\frac{16}{25}\left(\frac{1}{3}\left(\frac{11}{10}+1+0\right)\right)+\frac{8}{25}\left(\frac{1}{2}+\frac{11}{60}\right)+\frac{1}{25}\left(\frac{2}{3}\right)=\frac{520}{750}.$$

It is therefore not a profitable deviation. Furthermore, she has no incentive to deviate to other rankings such as (c, a, b) or (c, b, a).

The expected payoff to every student, before knowing their own true preferences, is:

$$\frac{320}{750}\frac{4}{5}+\frac{545}{750}\frac{1}{5}=\frac{365}{750}.$$

Remark A.3. *Note that the two scenarios, (1) and (2), result in the same payoffs under DA.*

Remark A.4. *In both scenarios, there is a positive probability that a type-$(1, 0.1, 0)$ student is matched with school B when there is at least one type-$(1, 1.1, 0)$ student.*

A.5 Scenario (3): Unknown Preferences (*ex ante*)

IA: Under IA, the unique symmetric equilibrium is that everyone plays $\sigma_{IA}^{(3)} = (a, b, c)$. The expected payoff of this strategy is:

$$\frac{1}{3}\left(1+\left(\frac{1}{5}\frac{11}{10}+\frac{4}{5}\frac{1}{10}\right)+0\right)=\frac{13}{30}=\frac{325}{750}.$$

If a student deviates to (b, a, c), her payoff is:

$$\left(\frac{1}{5}\frac{11}{10}+\frac{4}{5}\frac{1}{10}\right)=0.3=\frac{225}{750}.$$

Remark A.5. *In Scenario (2), the payoff is $\frac{397}{750}$ which is higher than that of Scenario (3), $\frac{225}{750}$.*

Remark A.6. *Comparing Scenarios (1), (2), and (3), we can improve the social welfare by making it easier for students to learn their preferences and then transforming (3) into (2) or (1) under IA.*

DA: The unique symmetric equilibrium under DA is that everyone plays $\sigma_{DA}^{(3)} = (a, b, c)$.

The expected payoff of this strategy is:

$$\frac{1}{3}\left(1+\left(\frac{1}{5}\frac{11}{10}+\frac{4}{5}\frac{1}{10}\right)+0\right)=\frac{13}{30}=\frac{325}{750}.$$

If a student deviates to (b, a, c), her payoff is:

$$\frac{1}{5}\left(\frac{2}{3}\frac{11}{10}\right) + \frac{4}{5}\left(\frac{2}{3}\frac{1}{10}\right) = 0.2 = \frac{150}{750}.$$

Remark A.7. *In Scenario (2), the payoff is* $\frac{365}{750}$ *which is higher than that of Scenario (3),* $\frac{325}{750}$.

Remark A.8. *Comparing Scenarios (1), (2), and (3), we can improve the social welfare by making it easier for students to learn their preferences and then transforming (3) into (2) or (1) under DA.*

Remark A.9. *The benefit of providing free information about own preferences is higher under IA.*

Remark A.10. *In Scenarios (3), IA achieves the same outcome as DA.*

Next, we discuss students' incentives to acquire information about one's own preferences.

A.6 Scenario (4): (3) + acquisition of information about one's own preferences

IA: Now suppose that students know only the distribution of their own and others' preferences. We consider their incentives to acquire information about their own preferences.

After acquiring information, both informed and uninformed students know how many others are informed. However, informed students know their own preferences, while uninformed students only know the distribution of preferences. Therefore, we consider willingness to pay (WTP) for information about own preferences in each of the three cases:

$$\begin{aligned} w_0^{own} &: \text{ when no other informed students;} \\ w_1^{own} &: \text{ when there is another informed student;} \\ w_2^{own} &: \text{ when there are two other informed students.} \end{aligned}$$

Table A.4 summarizes the equilibrium strategies and payoffs for informed and uninformed players.

Table A.4: Willingness to pay for information about own payoffs under IA

# of Players		Strategy:	Strategy: Informed		Ex Ante Payoff		Willingness to
Informed	Uninformed	Uninformed	(1,0.1, 0)	(1, 1.1, 0)	Informed	Uninformed	pay for info
0	3	(a, b, c)	-	-	-	$\frac{325}{750}$	$\frac{60}{750}$
1	2	(a, b, c)	(a, b, c)	(b, a, c)	$\frac{385}{750}$	$\frac{335}{750}$	$\frac{49.5}{750}$
2	1	(a, b, c)	(a, b, c)	(b, a, c)	$\frac{384.5}{750}$	$\frac{358}{750}$	$\frac{39}{750}$
3	0	-	(a, b, c)	(b, a, c)	$\frac{397}{750}$	-	

In the current setting, we focus on overt information acquisition. Namely, all students, informed and uninformed, know how many students in total are informed. Note that, for uninformed students, knowing or not knowing how many students are informed does not change their strategy.

Our overt-information-acquisition approach possibly provides a lower bound on information acquisition regarding one's own preferences. That is, one always has a greater incentive to acquire information covertly and choose to make it public only if she finds it profitable. Besides, the information acquisition in our setting is purely about one's own preferences, while all other information is costless.

When no other students are informed and a student acquires this information, the unique equilibrium in the school choice game is:

$$\begin{aligned}(One)\ Informed &: \sigma\left((1,1.1,0)\right) = (b,a,c) \text{ and } \sigma\left((1,0.1,0)\right) = (a,b,c)\,; \\ (Two)\ Uninformed &: (a,b,c)\,,\end{aligned}$$

The informed student obtains an expected payoff:

$$\frac{1}{5}\frac{11}{10} + \frac{4}{5}\left(\frac{1}{3}\left(\frac{1}{10} + 1 + 0\right)\right) = \frac{385}{750}.$$

When she chooses not to acquire information, the game is returned to Scenario (3) and her expected payoff is $\frac{325}{750}$. Therefore, given there is no other informed student, her WTP for the information is:

$$w_0^{own} = \frac{385}{750} - \frac{325}{750} = \frac{60}{750}.$$

If there is one informed student already, an additional student acquires this information, and the game has two informed players and one uninformed. The unique equilibrium in this case is:

$$\begin{aligned}\text{(Two) Informed} &: \sigma\left((1,1.1,0)\right) = (b,a,c) \text{ and } \sigma\left((1,0.1,0)\right) = (a,b,c)\,; \\ \text{(One) Uninformed} &: (a,b,c)\,.\end{aligned}$$

Informed students obtain an expected payoff:

$$\frac{1}{5}\left(\frac{1}{5}\frac{1}{2}\frac{11}{10} + \frac{4}{5}\frac{11}{10}\right) + \frac{4}{5}\left(\frac{1}{5}\frac{1}{2} + \frac{4}{5}\frac{11}{30}\right) = \frac{384.5}{750}.$$

If the student chooses not to acquire information, she plays against one informed and one uninformed players. The equilibrium is discussed above, and her payoff as an uninformed player is:

$$\frac{1}{5}\left(\frac{1}{5}\frac{1}{2} + \frac{4}{5}\frac{21}{30}\right) + \frac{4}{5}\left(\frac{1}{5}\frac{1}{2} + \frac{4}{5}\frac{11}{30}\right) = \frac{335}{750}$$

This implies that the WTP for information in this case is:

$$w_1^{own} = \frac{384.5}{750} - \frac{335}{750} = \frac{49.5}{750}.$$

When the other two students are informed, if the third student also decides to acquire this information, the game turns into one with three informed players as in Scenario (2). We know that her expected payoff is $\frac{397}{750}$. If she decides not to do so, she remains uninformed and plays against two informed players. The equilibrium is discussed above and her expected payoff is:

$$\frac{1}{5}\left(\frac{16}{25}\left(\frac{1}{3}\left(\frac{11}{10}+1+0\right)\right)+\frac{8}{25}\left(\frac{1}{2}(1+0)\right)+\frac{1}{25}(1)\right)$$
$$+\frac{4}{5}\left(\frac{16}{25}\left(\frac{1}{3}\left(\frac{1}{10}+1+0\right)\right)+\frac{8}{25}\left(\frac{1}{2}(1+0)\right)+\frac{1}{25}(1)\right)=\frac{358}{750}$$

Therefore, the WTP is:

$$w_2^{own}=\frac{397}{750}-\frac{358}{750}=\frac{39}{750}.$$

Remark A.11. *The WTP depends on the number of informed students. When the cost is lower than w_2^{own}, all students choose to be informed.*

Remark A.12. *When more students are informed, the incentive to acquire information is lower.*

Remark A.13. *Information acquisition has externalities. Namely, when more students are informed, the payoffs to uninformed students are higher.*

Remark A.14. *If we only elicit one number for the WTP, a student reports a number in $\left[\frac{39}{750},\frac{60}{750}\right]$, because her belief is a probability distribution over the three possible realizations, i.e., playing against another 0-2 informed students.*

DA: Now we consider DA. Students only know the distribution of their own and others' preferences. Table A.5 summarizes the equilibrium strategies and expected payoffs for informed and uninformed players under DA.

Table A.5: Willingness to Pay for Information about Own Payoffs under DA

# of Players		Strategy:	Strategy: Informed		Ex Ante Payoff		Willingness to
Informed	Uninformed	Uninformed	(1,0.1, 0)	(1, 1.1, 0)	Informed	Uninformed	pay for info
0	3	(a, b, c)	-	-	-	$\frac{325}{750}$	$\frac{5}{750}$
1	2	(a, b, c)	(a, b, c)	(b, a, c)	$\frac{330}{750}$	$\frac{342.5}{750}$	$\frac{5}{750}$
2	1	(a, b, c)	(a, b, c)	(b, a, c)	$\frac{347.5}{750}$	$\frac{360}{750}$	$\frac{5}{750}$
3	0	-	(a, b, c)	(b, a, c)	$\frac{365}{750}$	-	

When no other students are informed and a student acquires this information, the unique equilibrium in the school choice game is:

$$(One)\ Informed: \sigma\left((1,1.1,0)\right)=(b,a,c) \text{ and } \sigma\left((1,0.1,0)\right)=(a,b,c);$$
$$(Two)\ Uninformed: (a,b,c),$$

The informed student obtains an expected payoff:

$$\frac{1}{5}\left(\frac{11}{10}\frac{2}{3}\right)+\frac{4}{5}\left(\frac{1}{3}\left(\frac{1}{10}+1+0\right)\right)=\frac{330}{750}.$$

If she chooses not to acquire information, the game is returned to Scenario (3) and her expected payoff is $\frac{325}{750}$. Therefore, given there is no other informed student, her WTP for the information is:

$$w_0^{own}=\frac{330}{750}-\frac{325}{750}=\frac{5}{750}.$$

If there is one informed student already, an additional student acquires this information, and the game has two informed players and one uninformed. The unique equilibrium in this case is:

$$\begin{aligned}(Two)\ Informed &: \sigma\left((1,1.1,0)\right)=(b,a,c) \text{ and } \sigma\left((1,0.1,0)\right)=(a,b,c);\\ (One)\ Uninformed &: (a,b,c).\end{aligned}$$

Informed students obtain an expected payoff:

$$\frac{1}{5}\left(\frac{1}{5}\left(\frac{1}{2}\frac{11}{10}+\frac{1}{6}\right)+\frac{4}{5}\left(\frac{11}{10}\frac{2}{3}\right)\right)+\frac{4}{5}\left(\frac{1}{5}\left(\frac{1}{2}+\frac{1}{60}\right)+\frac{4}{5}\left(\frac{11}{30}\right)\right)=\frac{347.5}{750}.$$

If the student chooses not to acquire information, she plays against one informed and one uninformed players. The equilibrium is discussed above, and her payoff as an uninformed player is:

$$\frac{1}{5}\left(\frac{1}{5}\left(\frac{1}{2}+\frac{11}{60}\right)+\frac{4}{5}\frac{21}{30}\right)+\frac{4}{5}\left(\frac{1}{5}\left(\frac{1}{2}+\frac{1}{60}\right)+\frac{4}{5}\frac{11}{30}\right)=\frac{342.5}{750}$$

This implies that the WTP for information in this case is:

$$w_1^{own}=\frac{347.5}{750}-\frac{342.5}{750}=\frac{5}{750}.$$

When the other two students are informed, if the third student also decides to acquire this information, the game turns into one with three informed players as in Scenario (2). We know that her expected payoff is $\frac{365}{750}$. If she decides not to do so, she remains uninformed and plays against two informed players. The equilibrium is discussed above and her expected payoff is:

$$\begin{aligned}&\frac{1}{5}\left(\frac{16}{25}\left(\frac{1}{3}\left(\frac{11}{10}+1+0\right)\right)+\frac{8}{25}\left(\frac{1}{2}+\frac{11}{60}\right)+\frac{1}{25}\left(\frac{2}{3}\right)\right)\\ +&\frac{4}{5}\left(\frac{16}{25}\left(\frac{1}{3}\left(\frac{1}{10}+1+0\right)\right)+\frac{8}{25}\left(\frac{1}{2}+\frac{1}{60}\right)+\frac{1}{25}\left(\frac{2}{3}\right)\right)=\frac{360}{750}\end{aligned}$$

Therefore, the WTP is:

$$w_2^{own}=\frac{365}{750}-\frac{360}{750}=\frac{5}{750}.$$

Remark A.15. *The WTP is independent of the number of informed students.*

Remark A.16. *Information acquisition has very large externalities.*

Remark A.17. *If we only elicit one number for WTP, a student reports* $\frac{5}{750}$.

A.7 Scenario (5): (2) + acquisition of information about others' preferences

IA: Now suppose everyone knows her own preferences but not others', while the distribution of preferences is common knowledge. With some abuse of terminology, a student is informed if she knows the realization of others' preferences and whether each student is informed or not. An uninformed student knows her own preferences, but neither the others' preference realizations nor how many are informed.

Here, two pieces of information, i.e., other students' preferences and whether they are informed or not, are always acquired together. As we hypothesize that researching others' preferences is wasteful given independent preferences, we thus study cases where the incentives for wasteful information acquisition is high.

Note that a type-$(1, 0.1, 0)$ student has no incentive to acquire information. Therefore, the discussion of information acquisition is conditional on one's own type being $(1, 1.1, 0)$.

WTP for information about others' preferences can be similarly defined in the following three cases:

$$\begin{aligned} w_0^{other} &: \text{ when no other informed students;} \\ w_1^{other} &: \text{ when there is another informed student;} \\ w_2^{other} &: \text{ when there are two other informed students.} \end{aligned}$$

Table A.6 summarizes the equilibrium strategies and expected payoffs for informed and uninformed players under IA.

Table A.6: Willingness to pay for information about others' payoffs under IA

# of Players		Expected Payoff		Exp. Payoff to Type-(1,1.1,0)		WTP for info
Informed	Uninformed	Informed	Uninformed	Informed	Uninformed	given type-(1,1.1,0)
0	3	-	$\frac{397}{750}$	-	$\frac{681}{750}$	$\frac{9}{750}$
1	2	$\frac{398.8}{750}$	$\frac{396.1}{750}$	$\frac{690}{750}$	$\frac{676.5}{750}$	$\frac{0.6428}{750}$
2	1	$\frac{396.22857}{750}$	$\frac{398.54}{750}$	$\frac{677.14286}{750}$	$\frac{688.71}{750}$	0
3	0	$\frac{397}{750}$	-	$\frac{681}{750}$	-	

When there are no other informed students, the third student can stay uninformed and obtain $\frac{397}{750}$ *ex ante*, or $\frac{681}{750}$ conditional on being type $(1, 1.1, 0)$, as in Scenario (2). If she acquires information about others and becomes informed, the school choice game has the following equilibrium:

$$(Two)\ Uninformed : \sigma\left((1,1.1,0)\right) = (b,a,c)\,; \sigma\left((1,0.1,0)\right) = (a,b,c)\,;$$

and the informed player's strategies are summarized in Table A.7:

Table A.7: Equilibrium strategies of the informed player when others are uninformed under IA

Others' Preferences	Ex Ante Probability	Action: Informed Player (1, 0.1, 0)	Action: Informed Player (1, 1.1, 0)	Ex Post Payoff: Informed Player (1, 0.1, 0)	Ex Post Payoff: Informed Player (1, 1.1, 0)
(1, 0.1, 0) (1, 0.1, 0)	16/25	(a, b, c)	(b, a, c)	11/30	11/10
(1, 1.1, 0) (1, 0.1, 0)	8/25	(a, b, c)	(b, a, c)	1/2	11/20
(1, 1.1, 0) (1, 1.1, 0)	1/25	(a, b, c)	(a, b, c)	1	1

The expected payoff to the informed player is:

$$\frac{4}{5}\left(\frac{11}{30}\frac{16}{25}+\frac{1}{2}\frac{8}{25}+\frac{1}{25}\right)+\frac{1}{5}\left(\frac{11}{10}\frac{16}{25}+\frac{11}{20}\frac{8}{25}+\frac{1}{25}\right)=\frac{4}{5}\frac{326}{750}+\frac{1}{5}\frac{690}{750}=\frac{398.8}{750}.$$

Therefore, conditional on being type $(1,1.1,0)$, the WTP is:

$$w_0^{other}=\frac{690}{750}-\frac{681}{750}=\frac{9}{750}$$

The ex ante payoff to uninformed players, given that there is one informed student, is:

$$\frac{4}{5}\left(\frac{11}{30}\frac{16}{25}+\frac{1}{2}\frac{8}{25}+\frac{1}{25}\right)+\frac{1}{5}\left(\frac{11}{10}\frac{16}{25}+\frac{11}{20}\frac{8}{25}+\frac{11}{20}\frac{1}{25}\right)=\frac{4}{5}\frac{326}{750}+\frac{1}{5}\frac{676.5}{750}=\frac{396.1}{750}.$$

They have no incentive to deviate, and they are worse off than in Scenario (2).

When there is one other informed student, the third student can stay uninformed and obtain $\frac{396.1}{750}$ *ex ante*, or $\frac{676.5}{750}$ when being type $(1,1.1,0)$ as above. If she acquires information about others and becomes informed, the school choice game has the following equilibrium in pure strategies:

$$(One)\ Uninformed : \sigma\left((1,1.1,0)\right) = (b,a,c)\,; \sigma\left((1,0.1,0)\right) = (a,b,c)\,;$$

and the informed player's strategy is presented in Table A.8:

The expected payoff to an informed player is:

$$\frac{4}{5}\left(\frac{11}{30}\frac{16}{25}+\frac{1}{2}\frac{8}{25}+\frac{1}{25}\right)+\frac{1}{5}\left(\frac{11}{10}\frac{16}{25}+\frac{11}{20}\frac{8}{25}+\frac{4}{7}\frac{1}{25}\right)=\frac{4}{5}\frac{326}{750}+\frac{1}{5}\frac{158}{175}=\frac{396.22857}{750}.$$

Table A.8: Equilibrium strategies of the informed student when another student is informed under IA

Others' Preferences		Ex Ante	Action: Informed Player		Ex Post Payoff: Informed Player	
Uninformed	Informed	Probability	(1,0.1, 0)	(1, 1.1, 0)	(1, 0.1, 0)	(1, 1.1, 0)
(1, 0.1, 0)	(1, 0.1, 0)	16/25	(a, b, c)	(b, a, c)	11/30	11/10
(1, 1.1, 0)	(1, 0.1, 0)	4/25	(a, b,c)	(b, a, c)	1/2	11/20
(1, 0.1, 0)	(1, 1.1, 0)	4/25	(a, b,c)	(b, a, c)	1/2	11/20
(1, 1.1, 0)	(1, 1.1, 0)	1/25	(a, b,c)	(a, b, c) w/ prob. 6/7[a] (b, a, c) w/ prob. 1/7[a]	1	4/7

a. We may allow one informed student to play (a,b,c) and the other informed to play (b,a,c), which is a pure-strategy Nash equilibrium. When either of the two informed students has the same probability to play (a,b,c), the expected payoff of everyone is $31/40$ ($> 4/7$). This leads to a type-(1,1.1,0) student willing to pay 6.75/750 to become informed, given that there is only one more informed student. Moreover, this makes the third uninformed student willing to pay $4.5/750$ to be informed. In any case, the interval prediction of WTP for information about others' preferences, which is $[0, 9/750]$ for a type-(1,1.1,0) student, includes all these values.

Therefore, conditional on type $(1, 1.1, 0)$, the WTP given there is another informed agent is:

$$w_1^{other} = \frac{158}{175} - \frac{676.5}{750} = \frac{0.6428}{750}.$$

When two other students are informed, if the third chooses to be informed, we are back to Scenario (1). Conditional on being type $(1, 1.1, 0)$, her payoff is $\frac{681}{750}$ if informed. When two other students are informed, the third uninformed student has a payoff of:

$$\begin{aligned}&\frac{4}{5}\left(\frac{11}{30}\frac{16}{25} + \frac{1}{2}\frac{8}{25} + \frac{1}{25}\right) + \frac{1}{5}\left(\frac{11}{10}\frac{16}{25} + \frac{11}{20}\frac{8}{25} + \frac{46.9}{49}\frac{1}{25}\right)\\ =&\frac{4}{5}\frac{326}{750} + \frac{1}{5}\frac{688.71}{750} = \frac{398.54}{750}.\end{aligned}$$

Therefore,

$$w_2^{other} = \frac{681}{750} - \frac{688.71}{750} < 0.$$

That is, when the other two students are informed, the third student does not have an incentive to acquire information.

Remark A.18. *When only one number for WTP is elicited, a type-*$(1, 1.1, 0)$ *student reports a number in* $\left[0, \frac{9}{750}\right]$. *Averaging over all student ex ante, the WTP for information about others' preferences is in* $[0, \frac{1.8}{750}]$.

DA: Since truthful reporting is a dominant strategy, there is no incentive to know others' preferences.

Appendix B Equilibrium analyses with risk-averse students

This appendix compares risk-neutral and risk-averse students in terms of their WTP for information. While risk-neutral students have the same cardinal preferences as before (Table 1), we use a specific parameterization for risk-averse students' von Neumann-Morgenstern utilities associated with each schools (Table B.1). Our computation can generalize to other functional forms.

Table B.1: Preference/Payoff Table for Risk-Averse Students

Students	$s = a$	$s = b$	$s = c$
1	1	$\sqrt{0.1}$w/ prob. 4/5; $\sqrt{1.1}$w/ prob. 1/5	0
2	1	$\sqrt{0.1}$ w/ prob. 4/5; $\sqrt{1.1}$w/ prob. 1/5	0
3	1	$\sqrt{0.1}$ w/ prob. 4/5; $\sqrt{1.1}$w/ prob. 1/5	0

In the following, we evaluate the *ex ante* welfare/payoff, i.e., before the realization of the utility associated with school B. Note that ex ante, the expected payoff of being assigned to B is 0.463 ($\approx \frac{4*\sqrt{0.1}}{5} + \frac{1*\sqrt{1.1}}{5}$) and is better than 1/3 of a for any student.[22]

Conclusion B.1. *WTP for own values is lower for risk-averse students; WTP for others' values is similar when measured as the percentage of expected utilities, but is much lower when measured in dollars.*

B.1 Information about Own Values

Table B.2 tabulates the equilibrium WTP measured in dollars, as well as a percentage of the expected utility under complete information, and under no information.

Table B.2: WTP for information on own values: Risk-averse and risk-neutral students under IA

# of Other	In Dollars		Pctg. of Complete Info EU		Pctg. of no Info EU	
Informed Players	Averse	Neutral	Averse	Neutral	Averse	Neutral
0	0.077	0.080	13%	15%	15%	18%
1	0.062	0.066	11%	12%	12%	15%
2	0.049	0.052	8%	10%	9%	12%

Notes: WTP in dollars with risk aversion is calculated as follows: we first obtain the certainty equivalence in dollars of the two expected utilities and then take the difference.

In Table B.2, the complete information expected utility with risk averse under IA is 0.558, while the one under no information is 0.488. The corresponding expected values for the risk neutral students are $\frac{397}{750} = 0.529$ and $\frac{325}{790} = 0.411$, respectively.

[22] If $u(x) = \frac{x^{(1-r)}}{1-r}$, the expected utility from being matched with B is increasing in r which is also the coefficient of relative risk aversion.

Table B.3: WTP for information on own values: Risk-averse and risk-neutral students under DA

# of Other Informed Players	In Dollars		Pctg. of Complete Info EU		Pctg. of no Info EU	
	Averse	Neutral	Averse	Neutral	Averse	Neutral
0	0.003	0.007	0.57%	1.37%	0.61%	1.54%
1	0.004	0.007	0.57%	1.37%	0.61%	1.54%
2	0.004	0.007	0.57%	1.37%	0.61%	1.54%

Notes: WTP in dollars with risk aversion is calculated as follows: we first obtain the certainty equivalence in dollars of the two expected utilities and then take the difference.

B.2 Information about others' values

Note that the WTP for information given one's type being $(1, 0.1, 0)$ is always zero. Therefore, the table below is conditional on the student being type $(1, 1.1, 0)$.

Table B.4: WTP for information on others' values: Risk-averse & risk-neutral students under IA

# of Other Informed Players	In Dollars		Pctg. of Complete Info EU		Pctg. of no Info EU	
	Averse	Neutral	Averse	Neutral	Averse	Neutral
0	0.023	0.012	2%	2%	3%	3%
1	< 0	0.001	-	0%	-	0%
2	< 0	< 0	-	-	-	-

Notes: WTP in dollars with risk aversion is calculated as follows: we first obtain the certainty equivalence in dollars of the two expected utilities and then take the difference.

Appendix C Experimental Instructions: DA, OwnValue

This is an experiment in the economics of decision making. In this experiment, we simulate a procedure to allocate students to schools. The procedure, payment rules, and student allocation method are described below. The amount of money you earn will depend upon the decisions you make and on the decisions other people make. Do not communicate with each other during the experiment. If you have questions at any point during the experiment, raise your hand and the experimenter will help you. At the end of the instructions, you will be asked to provide answers to a series of review questions. Once everyone has finished the review questions, we will go through the answers together.

Overview:

- There are 12 participants in this experiment.
- The experiment consists of three parts:
  - There will be 20 rounds of school ranking decisions and student allocations.
  - At the end of the 20 rounds, there will be a lottery experiment.
  - Finally, there will be a survey.
- At the beginning of each round, you will be randomly matched into four groups. Each group consists of three participants. Your payoff in a given round depends on your decisions and the decisions of the other two participants in your group.
- In this experiment, three schools are available for each group, school a, school B and school c. Each school has one slot. Each school slot will be allocated to one participant.
- **Your payoff** amount for each allocation depends on the school you are assigned to. These amounts reflect the quality and fit of the school for you.
  - If you are assigned to school a, your payoff is 100 points.
  - If you are assigned to school B, your payoff is either 110 points or 10 points, depending on a random draw. Specifically,
    - with 20% chance, your payoff is 110 points;
    - with 80% chance, your payoff is 10 points.
  - If you are assigned to school c, your payoff is 0.
- **Your total payoff** equals the sum of your payoffs in all 20 rounds, plus your payoff from the lottery experiment. Your earnings are given in points. At the end of the experiment you will be paid based on the exchange rate,

\$1 = 100 points.

In addition, you will be paid \$5 for participation, and up to \$2.00 for answering the Review Questions correctly. Everyone will be paid in private and you are under no obligation to tell others how much you earn.

Are there any questions?

Procedure for the first 10 rounds:

- Every round, you will be asked to rank the schools twice:
  - Ranking without information (on your school B value): you will rank the schools without knowing the realization of your value for school B;
  - Ranking with information (on your school B value): the computer will first inform you of your school B value, and then ask you to rank the schools.
- **Ranking without information** consists of the following steps:
  - The computer will randomly draw the value of school B for each participant independently, but will not inform anyone of his or her value.
  - Without knowing the realization of school B value, every participant submits his or her school ranking.
  - The computer will then generate a lottery, and allocate the schools according to the Allocation Method described below.
  - The allocation results will not be revealed till the end of the round.
- **Ranking with information** consists of the following steps:
  - The computer will randomly draw the value of school B for each participant independently, and inform everyone of his or her school B value.
  - After knowing his or her school B value, every participant submits his or her school ranking.
  - After receiving the rankings, the computer will generate a lottery, and allocate the schools according to the Allocation Method described below.
- **Feedback**: At the end of each round, each participant receives the following feedback for each of the two rankings: your and your matches' school B values, rankings, lottery numbers, assigned schools, and earnings.
- At the beginning of each round, the computer randomly decides the order of the two rankings:

- with 50% chance, you will rank the schools without information first;
- with 50% chance, you will rank the schools with information first;

- The process repeats for 10 rounds.

Allocation Method

- **The lottery**: the priority of each student is determined by a lottery generated before each allocation. Every student is equally likely to be the first, second or third in the lottery.
- **The allocation of schools is described by the following method**:
  - An application to the first ranked school is sent for each participant.
  - Throughout the allocation process, a school can hold no more applications than its capacity.

    If a school receives more applications than its capacity, then it temporarily retains the student with the highest priority and rejects the remaining students.
  - Whenever an applicant is rejected at a school, his or her application is sent to the next choice.
  - Whenever a school receives new applications, these applications are considered together with the retained application for that school. Among the retained and new applications, the one with the highest priority is temporarily on hold.
  - The allocation is finalized when no more applications can be rejected.

    Each participant is assigned to the school that holds his or her application at the end of the process.

Note that the allocation is temporary in each step until the last step.

Are there any questions?

An Example:

We will go through a simple example to illustrate how the allocation method works. This example has the same number of students and schools as the actual decisions you will make. You will be asked to work out the allocation of this example for Review Question 1.

Students and Schools: In this example, there are three students, 1-3, and three schools, A, B, and C.

Student ID Number: $1, 2, 3$	Schools: A, B, C

Slots: There is one slot at each school.

School	Slot
A	☐
B	☐
C	☐

Lottery: Suppose the lottery produces the following order:

$\boxed{1 - 2 - 3}$

Submitted School Rankings: The students submit the following school rankings:

	1st Choice	2nd Choice	3rd Choice
Student 1	A	B	C
Student 2	A	B	C
Student 3	B	A	C

The allocation method consists of the following steps: Please use this sheet to work out the allocation and enter it into the computer for Review Question 1.

Step 1 (temporary): Each student applies to his/her first choice. If a school receives more applications than its capacity, then it temporarily holds the application with the highest priority and rejects the remaining students.

Applicants		School		Hold	Reject
1, 2	⟶	A	⟶	☐	
3	⟶	B	⟶	☐	
	⟶	C	⟶	☐	

Step 2 (temporary): Each student rejected in Step 1 applies to his/her next choice. When a school receives new applications, these applications are considered together with the application on hold for that school. Among the new applications and those on hold, the one with the highest priority is on hold, while the rest are rejected.

Applicants		School		Hold	Reject
	⟶	A	⟶	□	
	⟶	B	⟶	□	
	⟶	C	⟶	□	

Step 3 (temporary): Each student rejected in Step 2 applies to his/her next choice. Again, new applications are considered together with the application on hold for each school. Among the new applications and those on hold, the one with the highest priority is on hold, while the rest are rejected.

Applicants		School		Hold	Reject
	⟶	A	⟶	□	
	⟶	B	⟶	□	
	⟶	C	⟶	□	

Step 4 (final): Each student rejected in Step 3 applies to his/her next choice. No one is rejected at this step. All students on hold are accepted.

Applicants		School		Accept	Reject
	⟶	A	⟶	□	
	⟶	B	⟶	□	
	⟶	C	⟶	□	

The allocation ends at Step 4.

- Please enter your answer into the computer for Review Question 1.
- Afterwards, you will be asked to answer other review questions. When everyone is finished with them, we will go through the answers together.
- Feel free to refer to the experimental instructions before you answer any question. Each correct answer is worth 20 cents, and will be added to your total earnings.

Review Questions 2 - 7

2. How many participants are there in your group each round?
3. True or false: You will be matched with the same two participants each round.
4. Everyone has an equal chance of being the first, second or third in a lottery.

5. True or false: The lottery is fixed for the entire 20 rounds.
6. True or false: If you are not rejected at a step, then you are accepted into that school.
7. True or false: The allocation is final at the end of each step.

We are now ready to start the first 10 rounds. Feel free to earn as much as you can. Are there any questions?

Procedure for the second 10 rounds:

- Every round, you will again be asked to rank the schools twice.
- **Ranking without information** is identical to that in the first ten rounds.
- **Ranking with information**, however, will be different. We will elicit your willingness-to-pay for your school B value before you submit your ranking in each round. That is, the information about your school B value is no longer free. Specifically,
  - The computer will randomly draw the value of school B for each participant independently.
  - You will be asked your **willingness to pay** for this information. You can enter a number in the interval of $[0, 15]$ points, inclusive, to indicate your willingness to pay.
  - After everyone submits their willingness to pay, the computer will randomly draw a number for each participant independently. The number will be between 0 and 15, inclusive, with an increment of 0.01, with each number being chosen with equal probability.
    * If your willingness to pay is greater than the random number, you will pay the random number as your price to obtain your school B value. The computer will reveal your school B value and charge you a price which equals the random number.
    * If your willingness to pay is below the random number, the computer will not reveal your school B value and you will not be charged a price.

    It can be demonstrated that, given the procedures we are using, it is best for you, in terms of maximizing your earnings, to report your willingness to pay for your school B value truthfully since doing anything else would reduce your welfare. So it pays to report your willingness to pay truthfully.
  - You will also be asked to **guess** the average willingness to pay of the other two participants in your group, again, in the interval of $[0, 15]$ points, inclusive.
  - You will be rewarded for guessing the average of your matches' willingness to pay correctly. Your payoff from guessing is determined by the squared error between your guess and the actual average, i.e., (your guess - the actual average)^2. Specifically, the computer will randomly choose a number between 0 and 49, with each number being chosen with equal probability. You will earn 5 points, if your squared error is below the

random number and zero otherwise. Therefore, you should try to guess as accurately as possible.

  – Regardless of whether you obtain your school B value, the computer will reveal the number of participant(s) in your group who have obtained their school B value(s).
  – Every participant submits his or her school ranking.
  – After everyone submits their rankings, the computer will generate a lottery, and allocate the schools according to the same Allocation Method used in the first ten rounds.

- **Feedback**: At the end of each round, each participant receives the same feedback for each of the two rankings as in the first ten rounds.

  In addition, for ranking with information, the computer will also tell you: your and your matches' willingness to pay, the actual prices paid, the random numbers, whether each participant in your group knows their school B values, the guesses, and guess earnings.

- The process repeats for 10 rounds.

Are there any questions? You can now proceed to answer review questions 8-10 on your computer. Recall each correct answer is worth 20 cents, and will be added to your total earnings. Again, feel free to refer to the instructions before you answer any question.

Review Questions 8 - 10

8. Suppose you submitted 1.12 as your willingness to pay to obtain your school B value, and the random number is 5.48. Do you get to know your school B value? What price do you pay?
9. Suppose you submitted 10.33 as your willingness to pay to obtain your school B value, and the random number is 8.37. Do you get to know your school B value? What price do you pay?
10. Suppose your guess for the average willingness to pay of the other two participants is 7, and the actual average is 10. The computer draws a random number, 14. What is your earning from your guess?

Lottery Experiment

Procedure

- **Making Ten Decisions**: On your screen, you will see a table with 10 decisions in 10 separate rows, and you choose by clicking on the buttons on the right, option A or option B, for each of the 10 rows. You may make these choices in any order and change them as much as you wish until you press the Submit button at the bottom.

- The money prizes are determined by the computer equivalent of throwing a ten-sided die. Each outcome, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, is equally likely. If you choose Option A in the row shown below, you will have a 1 in 10 chance of earning 200 points and a 9 in 10 chance of earning 160 points. Similarly, Option B offers a 1 in 10 chance of earning 385 points and a 9 in 10 chance of earning 10 points.

Decision	Option A	Option B	Your Choice
1	200 points if the die is 1 160 points if the die is 2-10	385 points if the die is 1 10 points if the die is 2-10	A or B

- **The Relevant Decision**: One of the rows is then selected at random, and the Option (A or B) that you chose in that row will be used to determine your earnings. Note: Please think about each decision carefully, since each row is equally likely to end up being the one that is used to determine payoffs.

  For example, suppose that you make all ten decisions and the throw of the die is 9, then your choice, A or B, for decision 9 below would be used and the other decisions would not be used.

Decision	Option A	Option B	Your Choice
9	200 points if the die is 1-9 160 points if the die is 10	385 points if the die is 1-9 10 points if the die is 10	A or B

- **Determining the Payoff**: After one of the decisions has been randomly selected, the computer will generate another random number that corresponds to the throw of a ten-sided die. The number is equally likely to be 1, 2, 3, ... 10. This random number determines your earnings for the Option (A or B) that you previously selected for the decision being used.

  For example, in Decision 9 below, a throw of 1, 2, 3, 4, 5, 6, 7, 8, or 9 will result in the higher payoff for the option you chose, and a throw of 10 will result in the lower payoff.

Decision	Option A	Option B	Your Choice
9	200 points if the die is 1-9 160 points if the die is 10	385 points if the die is 1-9 10 points if the die is 10	A or B
10	200 points if the die is 1-10	385 points if the die is 1-10	A or B

  For decision 10, the random die throw will not be needed, since the choice is between amounts of money that are fixed: 200 points for Option A and 385 points for Option B.

We encourage you to earn as much cash as you can. Are there any questions?

Appendix D Additional Analyses of Experimental Data

In this appendix, we first present the summary statistics of the experimental data (Table D.1) and then examine the robustness of our analyses in section 5.1 regarding WTP for information.

D.1 Willingness to Pay for Information: Robustness Checks

In section 5.1, we use a Tobit model to investigate the determinants of WTP for information. Here, we present the results from linear panel regressions that allow more flexible specifications and instrumental variables. In short, the following results are similar to those in the main text, indicating that the endogeneity issue is not a concern.

Corresponding to Table 4 in section 5.1, Table D.2 regresses subject-average WTP on treatment types and other controls. The two sets of results are qualitatively the same.

In comparison with the results from the random-effect Tobit model in Tables D.3 and 5, the next two tables provide the results from our analyses of the determinants of WTP in random and fixed effects panel linear regressions. In all specifications, our outcome variable is the subject-round WTP. The specification is as follows:

$$\begin{aligned} WTP_{i,t} = & \alpha_i + \beta_1 High\_B \times IA\_OtherValue_{i,t} + \beta_2 High\_B \times DA\_OtherValue_{i,t} \\ & + \beta_3 WTP\_Guess_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \end{aligned}$$

where i is the index for subjects and t for rounds (with each session); α_i is subject fixed effects; and all control variables are time-subject-specific. Other controls are the same as in section 5.1. Depending on whether the model is random or fixed effects, the interpretation of α_i is different.

The endogeneity of $WTP\_Guess_{i,t}$ is plausible if there are common shocks in round t that increase everyone's $WTP_{i,t}$ and $WTP\_Guess_{i,t}$. We address this issue with an IV approach where the lagged $WTP\_Average_{-i,t-1}$ is the instrumental variable. $WTP\_Average_{-i,t-1}$, i' opponents' WTP in round $t-1$, is correlated with $WTP\_Guess_{i,t}$, as a subject might rely on the opponents' WTP in the previous round to make her guess of others' WTP this round. Moreover, $WTP\_Average_{-i,t-1}$ should not affect her decision in round t directly, as opponents in each round are randomly drawn.

The fixed-effect results are presented in Table D.4. The first three columns are from OLS, while column 4 is from an IV regression, where the instrument for the potentially endogenous variable, $WTP\_Guess_{i,t}$, is $WTP\_Average_{-i,t-1}$. Column 5 shows the first-stage result.

When we consider $WTP\_Average_{-i,t-1}$ as an IV for use $WTP\_Guess_{i,t}$, column 5 presents the first-stage result which shows that $WTP\_Average_{-i,t-1}$ is positively correlated with $WTP\_Guess_{i,t}$ (significant at 1% level).

Column 4 is the IV regression result. Observationally, IV results are not very different from OLS results (column 3), although the coefficient on $WTP\_Guess_{i,t}$ is decreased. We next perform an endogeneity test. Under the null hypothesis that $WTP\_Guess_{i,t}$ can actually be treated as exogenous, the test statistic is distributed as chi-squared with degrees of freedom equal to one. It is defined as the difference of two Sargan-Hansen statistics: one for the IV regression, where the

Table D.1: Summary Statistics of Experimental Data

	Full Sample	Consistent Subjects in the Holt-Laury Lottery Choice Game[a]				
		All	IA		DA	
		Treatments	OwnValue	OtherValue	OwnValue	OtherValue
	(1)	(2)	(3)	(4)	(5)	(6)
WTP for info	4.42	4.24	6.44	4.32	4.17	1.84
	(4.57)	(4.56)	(4.87)	(4.68)	(4.30)	(2.86)
Guess of others' WTP	5.09	5.01	7.03	5.25	4.39	3.22
	(2.90)	(2.90)	(2.44)	(2.89)	(2.63)	(2.17)
Info Acquired	0.29	0.28	0.43	0.26	0.28	0.11
	(0.46)	(0.45)	(0.50)	(0.44)	(0.45)	(0.31)
High_B×IA_OtherValue	0.05	0.05	-	0.20	-	-
	(0.22)	(0.21)	-	(0.40)	-	-
High_B×DA_OtherValue	0.05	0.04	-	-	-	0.19
	(0.21)	(0.21)	-	-	-	(0.39)
Total cash payment after all rounds[b]	27.89	27.93	27.58	29.03	26.91	28.36
	(4.14)	(4.16)	(4.39)	(3.50)	(4.20)	(4.25)
% playing a dominated strategy w/ free info						
IA	0.50	0.39	0.90	0.64	–	–
	(2.71)	(2.26)	(2.67)	(3.61)	–	–
DA	4.70	4.01	–	–	8.54	7.37
	(11.16)	(10.51)	–	–	(13.50)	(13.94)
Costly-to-free	0.50	0.51	0.52	0.49	0.52	0.51
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Risk aversion	5.59	6.68	6.41	6.49	6.77	7.05
	(2.80)	(1.44)	(1.28)	(1.56)	(1.43)	(1.38)
Consistent in Holt-Laury	0.84	-	-	-	-	-
	(0.37)	-	-	-	-	-
Curiosity	4.20	3.87	5.47	4.35	3.51	2.01
	(4.95)	(4.86)	(5.46)	(5.06)	(4.55)	(3.39)
Demographics						
Female	0.54	0.54	0.44	0.56	0.55	0.60
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Graduate student	0.14	0.15	0.21	0.18	0.14	0.05
	(0.35)	(0.35)	(0.41)	(0.38)	(0.35)	(0.22)
Black	0.05	0.03	0.08	0.02	0.00	0.02
	(0.21)	(0.17)	(0.27)	(0.13)	(0.00)	(0.13)
Asian	0.36	0.40	0.41	0.33	0.48	0.35
	(0.48)	(0.49)	(0.49)	(0.47)	(0.50)	(0.48)
Hispanic	0.02	0.02	0.03	0.00	0.05	0.00
	(0.14)	(0.14)	(0.18)	(0.00)	(0.21)	(0.00)
Age	20.83	20.80	21.70	19.82	21.19	20.37
	(3.47)	(3.05)	(3.57)	(3.48)	(2.54)	(1.97)
# Observations	2592	2169	567	513	576	513
# Subjects	288	241	63	57	64	57

Notes: This table reports means and standard deviations (in parentheses) for the variables used in the main analysis. Corresponding to the regressions controlling for lagged variables, every subject's 9 rounds (2nd to 10th) with costly information acquisition are included, whereas the rounds with free information and the first round with costly information are excluded from in the calculation of these statistics.

a. A subject is not consistent in the Holt-Laury lottery choice game if she has more than one switching point or makes a dominated choice. Columns 2–6 exclude 47 inconsistent subjects.

b. This variable is the cash payment after all rounds measured at the subject level. In other words, its mean and standard deviation are calculated across subjects with each subject corresponding to one observation. Note that the "wealth" variable used in regression analyses measures the accumulated cash payment at the beginning of a round.

$WTP\_Guess_{i,t}$ is treated as endogenous, and one for the OLS regression, where $WTP\_Guess_{i,t}$ is treated as exogenous. It turns out that the test statistic is 1.64 (p-value 0.20), which leads us to

Table D.2: Determinants of Subject-Average WTP: Linear Regression

	(1) Full Sample	(2) Sub-sample	(3) Sub-sample	(4) Sub-sample
IA_OwnValue	6.56***	6.41***	5.68***	4.08
	(0.55)	(0.56)	(0.92)	(3.72)
IA_OtherValue	4.51***	4.31***	4.01***	2.20
	(0.48)	(0.54)	(0.93)	(3.82)
DA_OwnValue	4.44***	4.16***	3.75***	2.08
	(0.63)	(0.70)	(0.91)	(3.75)
DA_OtherValue	2.21***	1.92***	2.11**	0.53
	(0.30)	(0.27)	(0.95)	(3.74)
% playing a dominated strategy w/ free info				
IA			0.11	0.11
			(0.10)	(0.11)
DA			0.05***	0.05**
			(0.02)	(0.02)
Curiosity			0.29***	0.29***
			(0.05)	(0.05)
Costly-to-free			1.65***	1.59***
			(0.37)	(0.31)
Risk Aversion			-0.29**	-0.25
			(0.12)	(0.15)
Female				-0.75*
				(0.39)
Graduate Student				0.56
				(1.73)
Black				-1.76
				(1.45)
Asian				-0.48
				(0.39)
Hispanic				-1.84**
				(0.77)
N	288	241	241	241
R^2	0.65	0.63	0.73	0.75

Notes: The outcome variable is subject-level average WTP for information. Columns 2-4 exclude subjects with multiple switching points in the Holt-Laury lottery game or those who make inconsistent choices. Column 4 also includes the following controls: age, ACT score, SAT score, dummy for other non-white ethnicities/races, dummy for ACT score missing, dummy for SAT score missing, dummy for degree missing, dummy for age missing, dummy for ethnicity missing, and dummy for gender missing. Standard errors clustered at session level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

conclude that $WTP\_Guess_{i,t}$ is exogenous.

In summary, the results in Table D.4 are similar to those in Tables D.3 and 5 from a random effect Tobit model. Moreover, the IV results in column (3) are qualitatively similar to other results in Table D.4.

When we repeat the same analyses with random effect panel regressions, we obtain similar results (Table D.5).

Table D.3: Determinants of WTP: Random Effects Panel Tobit Analyses (Treatments pooled)

	(1)	(2)	(3)	(4)
IA_OwnValue	3.62**	3.48***	3.51**	3.37**
	(1.45)	(1.26)	(1.45)	(1.39)
IA_OtherValue	1.76	1.44	1.68	1.37
	(1.24)	(1.12)	(1.19)	(1.14)
DA_OwnValue	2.18**	2.06*	2.15*	2.03**
	(1.11)	(1.06)	(1.10)	(1.01)
High_B × IA_OtherValue	3.17***	3.16***	3.18***	3.17***
	(1.10)	(0.86)	(1.09)	(0.85)
High_B × DA_OtherValue	-0.69	-0.67	-0.68	-0.66
	(1.07)	(1.17)	(1.14)	(1.10)
$WTP\_Guess_{i,t}$: Guess of Opponents' WTP in t	0.79***	0.78***	0.79***	0.78***
	(0.14)	(0.14)	(0.14)	(0.14)
$WTP\_Guess_{i,t}$ × DA	0.21	0.23	0.20	0.22
	(0.19)	(0.18)	(0.19)	(0.19)
% playing a dominated strategy w/ free info				
IA	0.24*	0.26*	0.25*	0.26*
	(0.13)	(0.15)	(0.13)	(0.15)
DA	0.08***	0.08**	0.08***	0.08**
	(0.02)	(0.03)	(0.02)	(0.03)
Curiosity	0.39***	0.39***	0.39***	0.39***
	(0.06)	(0.06)	(0.06)	(0.06)
Costly-to-free	1.39*	1.23*	1.50**	1.35**
	(0.71)	(0.65)	(0.77)	(0.69)
Risk Aversion	-0.44**	-0.35	-0.43**	-0.34*
	(0.19)	(0.21)	(0.19)	(0.21)
Round	-0.04	-0.04	-0.06	-0.06
	(0.07)	(0.07)	(0.07)	(0.07)
Round × costly-to-free	-0.11	-0.10	-0.10	-0.10
	(0.10)	(0.09)	(0.10)	(0.10)
Accumulated wealth up to $t-1$			0.02	0.02
			(0.03)	(0.03)
Successfully acquired info in $t-1$			0.28	0.28
			(0.25)	(0.25)
Other demographical controls	No	Yes	No	Yes
# of observations	2169	2169	2169	2169
# of subjects	241	241	241	241

Notes: The regression sample includes only consistent subjects in the Holt-Laury lottery game. There are 241 subjects in this sample each of whom has 9 observations from rounds 2–10. Columns (2) and (4) include additional demographical controls: dummy for female, dummy for graduate student, dummy for black, dummy for Asian, dummy for Hispanic, dummy for other non-white ethnicities/races, age, ACT score, SAT score, dummy for ACT score missing, dummy for SAT score missing, dummy for degree missing, dummy for age missing, dummy for ethnicity missing, and dummy for gender missing. Standard errors clustered at session level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Decomposition based on Pooled Regression

Table 6 in section 5.1 presents the WTP decomposition based on Tobit models for each treatment. As a robustness check, we also present results based on pooled regressions (Table D.6). Although

Table D.4: Determinants of WTP: Linear Models with Fixed Effects and IV Results (Treatments pooled)

	FE (1)	FE (2)	IV (3)	$WTP\_Guess_{i,t}$ 1st Stage (4)	$WTP\_Guess_{i,t} \times DA$ 1st Stage (5)
High_B × IA_OtherValue	2.25**	2.25**	2.23***	-0.05	-0.06**
	(0.81)	(0.80)	(0.78)	(0.26)	(0.02)
High_B × DA_OtherValue	-0.09	-0.09	-0.10	-0.02	-0.02
	(0.44)	(0.44)	(0.39)	(0.24)	(0.24)
Round	-0.01	-0.02	-0.04	-0.12***	-0.09**
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Round × costly-to-free	-0.08	-0.08	-0.07	0.03	0.03
	(0.05)	(0.05)	(0.06)	(0.04)	(0.04)
Accumulated wealth up to $t-1$		0.01			
		(0.02)			
Successfully acquired info in $t-1$		-0.03			
		(0.22)			
"Endogenous" explanatory variables:					
Guess of Opponents' WTP in t	0.55***	0.55***	0.60***		
	(0.10)	(0.10)	(0.14)		
(Guess of Opponents' WTP in t) × DA	0.09	0.09	-0.27		
	(0.14)	(0.14)	(0.20)		
Instrumental variables:					
Average WTP of Opponents in $t-1$				0.14***	-0.00
				(0.02)	(0.00)
(Average WTP of Opponents in $t-1$) × DA				0.03	0.18***
				(0.02)	(0.02)
# of Observations	2169	2169	2169	2169	2169
# of Subjects	241	241	241	241	241
R^2	0.18	0.18	0.16	0.12	0.13

Notes: The outcome variable is WTP for information of each subject in each round. Regressions exclude subjects with multiple switching points or making dominated choices in the Holt-Laury lottery game and only include observations from rounds 2-10. Standard errors clustered at session level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
"Average WTP of Opponents in $t-1$" and its interaction with DA is used as IVs for "Guess of Opponents' WTP in t" and its interaction with DA (the 1st-stage results in columns 4 and 5, i.e., dependent variable = "Guess of others' WTP in t" in column 4, = "(Guess of others' WTP in t)×DA" in column 5). An endogeneity test for "Guess of Opponents' WTP in t" and its interaction with DA based on Sargan-Hansen statistics gives a p-value of 0.12. That is, we fail to reject the null hypothesis that the variables are exogenous.

results change to some extent, "Conformity" still explains the largest part of the WTP.

Table D.5: Determinants of WTP: Linear Models with Random Effects and IV Results (Treatments pooled)

	RE (1)	RE (2)	RE (3)	RE (4)	IV (5)	$WTP\_Guess_{i,t}$ 1st Stage (6)	$WTP\_Guess_{i,t} \times DA$ 1st Stage (7)
IA_OwnValue	1.76**	1.67**	1.42*	1.38*	0.73	3.25***	-2.79***
	(0.79)	(0.80)	(0.73)	(0.75)	(1.13)	(0.30)	(0.27)
IA_OtherValue	0.56	0.41	0.37	0.28	-0.57	1.68***	-2.79***
	(0.63)	(0.71)	(0.57)	(0.65)	(0.92)	(0.43)	(0.25)
DA_OwnValue	1.07***	0.97**	0.97**	0.87**	1.33**	0.62**	0.68*
	(0.39)	(0.40)	(0.39)	(0.39)	(0.54)	(0.31)	(0.37)
High_B × IA_OtherValue	2.29***	2.27***	2.36***	2.32***	2.24***	-0.04	-0.06**
	(0.82)	(0.82)	(0.86)	(0.84)	(0.64)	(0.26)	(0.03)
High_B × DA_OtherValue	-0.07	-0.06	-0.03	0.01	-0.09	-0.03	-0.04
	(0.44)	(0.44)	(0.44)	(0.44)	(0.43)	(0.24)	(0.23)
Round	-0.01	-0.01	-0.00	-0.00	-0.04	-0.12***	-0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Round × costly-to-free	-0.08	-0.08	-0.07	-0.07	-0.07	0.03	0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.04)	(0.04)
% playing a dominated strategy w/ free info							
IA	0.18**	0.20**	0.18**	0.20**	0.20	-0.11*	0.01
	(0.09)	(0.09)	(0.08)	(0.09)	(0.12)	(0.06)	(0.01)
DA	0.04**	0.03*	0.03**	0.03*	0.04**	0.03**	0.02**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Curiosity	0.22***	0.23***	0.21***	0.21***	0.25***	0.12***	0.04**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)
Costly-to-free	0.93**	0.80**	0.76*	0.61	1.11***	1.47***	0.67***
	(0.36)	(0.35)	(0.41)	(0.42)	(0.34)	(0.34)	(0.25)
Risk Aversion	-0.31***	-0.28**	-0.30***	-0.27**	-0.28**	0.05	-0.02
	(0.10)	(0.12)	(0.10)	(0.12)	(0.13)	(0.09)	(0.05)
Accumulated wealth up to $t-1$			-0.00	-0.01			
			(0.02)	(0.02)			
Successfully acquired info in $t-1$			0.66***	0.62***			
			(0.21)	(0.21)			
"Endogenous" explanatory variables:							
Guess of Opponents' WTP in t	0.59***	0.58***	0.62***	0.62***	0.55***		
	(0.09)	(0.10)	(0.08)	(0.09)	(0.13)		
(Guess of Opponents' WTP in t)×DA	0.09	0.09	0.07	0.09	-0.23		
	(0.12)	(0.13)	(0.11)	(0.12)	(0.20)		
Instrumental variables:							
Average WTP of opponents in $t-1$						0.15***	-0.00
						(0.01)	(0.00)
(Average WTP of opponents in $t-1$)×DA						0.03	0.18***
						(0.02)	(0.02)
Other Demographic Controls	No	Yes	No	Yes	Yes	Yes	Yes
# of Observations	2169	2169	2169	2169	2169	2169	2169
# of Subjects	241	241	241	241	241	241	241

Notes: The regression sample is the same as that in column 1 in Table 5. Each of the 241 subjects has 9 observations from 9 rounds. Estimates are from random effects panel Tobit models. All specifications include additional controls: dummy for female, dummy for graduate student, dummy for black, dummy for Asian, dummy for Hispanic, age, ACT score, SAT score, dummy for ACT score missing, dummy for SAT score missing, dummy for degree missing, dummy for age missing, dummy for ethnicity missing, and dummy for gender missing. Standard errors clustered at session level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
"Average WTP of Opponents in $t-1$" and its interaction with DA is used as IVs for "Guess of Opponents' WTP in t" and its interaction with DA (the 1st-stage results in columns 4 and 5, i.e., dependent variable = "Guess of others' WTP in t" in column 6, = "(Guess of others' WTP in t)×DA" in column 7). Without clustered standard errors, an endogeneity test for "Guess of Opponents' WTP in t" and its interaction with DA based on Hausman's specification test gives a p-value of 0.74. That is, we fail to reject the null hypothesis that the variables are exogenous.

Table D.6: Decomposition of Subject WTP for Information Based on the Pooled Regression

	IA OwnValue	IA OtherValue	DA OwnValue	DA OtherValue
WTP: data	**6.44**	**4.32**	**4.17**	**1.84**
	(4.87)	(4.68)	(4.30)	(2.86)
Model prediction[a]	6.28	4.11	4.17	1.79
	(2.77)	(2.83)	(2.81)	(1.84)
(i) Order effect[b]	0.72	0.57	1.25	0.64
	(0.31)	(0.32)	(0.79)	(0.57)
(ii) Learning over rounds[b]	0.29	0.24	0.94	0.48
	(0.28)	(0.26)	(0.70)	(0.50)
(iii) Conformity[b]	3.77	2.38	2.60	1.18
	(1.72)	(1.83)	(2.07)	(1.34)
(iv) % playing a dominated strategy w/ free info[b]	0.18	0.08	1.11	0.57
	(0.53)	(0.43)	(0.99)	(0.73)
(v) Curiosity[b]	1.72	1.22	1.62	0.71
	(1.74)	(1.51)	(1.60)	(1.10)
(vi) Risk aversion[b]	-0.36	-0.31	0.35	0.09
	(0.31)	(0.36)	(0.57)	(0.32)
Total Explained by factors (i)-(vi)[c]	**5.37**	**3.44**	**3.60**	**1.56**
	(2.68)	(2.57)	(2.76)	(1.81)
Residual WTP[d]	**1.06**	**0.88**	**0.56**	**0.28**
	(3.95)	(3.85)	(3.09)	(2.25)
Theoretical prediction[e]	**[5.2,8]**	**[0,0.24]**	**0.67**	**0.00**
# of observations	567	513	576	513
# of subjects	63	57	64	57

Notes: Decompositions are based on a random effects panel Tobit model that pools observations from all four treatments (column 1 in Table 5 or, equivalently, column 2 of Table D.3). This is in contrast to Table 6 which uses a separate regression for each treatment. The table reports the sample average, while standard deviations are in parentheses.

a. "Model prediction" is the predicted value of E(WTP) based on the corresponding estimated model, assuming that unobserved error terms are equal to zero. The predicted values are censored to $[0, 15]$.

b. The WTP explained by the corresponding factor is the difference between the model prediction with and without the factor. The former is predicted from the current values of all variables; the latter is calculated by setting the relevant variable value to zero (for factors "Order effect," "Conformity," "% playing a dominated strategy w/ free info," or "Curiosity") or setting the relevant variable to the counterfactual value (for "Risk aversion," we set the risk aversion measure to the risk-neutral value; for "Learning over round," we set "Round" to be the last round, i.e., "Round" $= 10$).

c. "Total Explained by factors (i)-(vi)" is the total WTP explained by the six factors above. Note that it is not the sum of the explained WTP of the six factors because of the censoring at 0 and 15.

d. "Residual WTP" is the difference between the observed WTP and the total WTP explained by the six factors.

e. The theoretical predictions are for risk neutral subjects.

Table D.7: Summary Statistics of Payments for Information among Subjects with $ZeroD_i = 0$

Treatment	# observations	Mean	Median	Std. deviation	Min	Max
IA OwnV	660	2.46	0	3.65	0	14.87
IA OtherV	650	1.45	0	2.78	0	14.32
DA OwnV	610	1.59	0	3.06	0	14.21
DA OtherV	520	0.67	0	1.75	0	10.44
Total	2440	1.59	0	3.01	0	14.87

D.3 Under-investment in Information Acquisition

We run the following linear probability model to investigate who are more likely to have a zero demand for information:

$$ZeroD_i = \alpha + \beta Demographics_i + OtherControls_i + \varepsilon_i, \tag{2}$$

where $Demographics_i$ includes the following list of variables: dummy for female, dummy for graduate student, dummy for black, dummy for Asian, dummy for Hispanic, age, ACT score, SAT score, dummy for ACT score missing, dummy for SAT score missing, dummy for degree missing, dummy for age missing, dummy for ethnicity missing, and dummy for gender missing. We include Curiosity in some of the regressions. We first pool all treatments together and then run the regressions separately for each treatment. In the pooled regressions, we also include as $OtherControls_i$ the dummy for IA OwnValue, IA OtherValue, DA OwnValue, and Costly-to-free. Table D.8 shows that none of the demographics is robustly correlated with $ZeroD_i$. However, Curiosity is negatively correlated with $ZeroD_i$, and the correlation is statistically significant.

When we account for the information acquisition cost incurred by subjects with non-zero demand for information, we obtain similar results, as the payments are on average low (Table D.7).

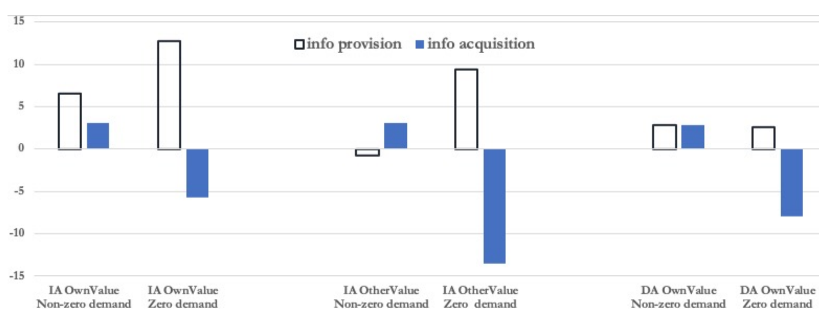

Figure D.1: Effects of Information Provision & Costly Acquisition on Payoffs

Notes: Payoffs are calculated relative to the case in which the information in question is not provided or not possible to be acquired. Payoffs are net of information acquisition costs. A subject has a "zero info demand" if her WTP is zero in every round.

With the results in Figure D.1, we test if the effects of information provision/acquisition are different for the two types of subjects. Our results coincide with those for revenues:

Table D.8: Linear Probability Model: Who has a zero demand for information?

	Full Sample		IA_OwnValue		IA_OtherValue		DA_OwnValue	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Curiosity		-0.02***		-0.01**		-0.02**		-0.02**
		(0.00)		(0.01)		(0.01)		(0.01)
Costly-to-free	-0.09	-0.08	-0.06	-0.06	-0.14*	-0.15*	-0.02	0.01
	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)
IA_OwnV	-0.05	-0.02						
	(0.05)	(0.05)						
IA_OtherV	-0.05	-0.03						
	(0.07)	(0.07)						
Female	0.10***	0.08**	0.09	0.05	0.07	0.05	0.11	0.10
	(0.03)	(0.03)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Graduate student	-0.13	-0.15	0.16	0.31	-0.17	-0.62	-0.44*	-0.43*
	(0.19)	(0.15)	(0.34)	(0.34)	(0.62)	(0.64)	(0.25)	(0.24)
Black	-0.15**	-0.13*	-0.13	-0.10	-0.03	-0.08	-0.17	-0.09
	(0.06)	(0.06)	(0.13)	(0.13)	(0.22)	(0.22)	(0.25)	(0.25)
Asian	0.02	0.04	0.07	0.09	0.06	0.07	-0.02	0.01
	(0.05)	(0.04)	(0.09)	(0.09)	(0.10)	(0.09)	(0.10)	(0.10)
Hispanic	0.21	0.21	-0.05	-0.03	0.00	0.00	0.33*	0.32*
	(0.16)	(0.17)	(0.23)	(0.22)	(.)	(.)	(0.19)	(0.18)
Other ethnicity	-0.13**	-0.13**	-0.11	-0.06	-0.19	-0.11	-0.17	-0.20
	(0.05)	(0.05)	(0.19)	(0.18)	(0.14)	(0.14)	(0.16)	(0.15)
Age	-0.01	-0.01	-0.00	0.00	-0.01	-0.02	0.03	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
ACT	0.00	0.00	0.01	0.01	0.03***	0.03***	-0.00	-0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
SAT	-0.00	-0.00	-0.00	-0.00	-0.00***	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.41	0.54**	-0.22	-0.29	0.38	1.03	-0.21	0.09
	(0.29)	(0.25)	(0.63)	(0.61)	(1.06)	(1.07)	(0.58)	(0.58)
N	216	216	72	72	72	72	72	72
R^2	0.12	0.19	0.15	0.22	0.25	0.31	0.34	0.39

Notes: The full sample includes subjects from the three treatments. Standard errors clustered at individual level are in parentheses. Additional controls include dummy for ACT score missing, dummy for SAT score missing, dummy for degree missing, dummy for age missing, dummy for ethnicity missing, and dummy for gender missing. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(i) **Effect of information provision**: The same as before.

(ii) **Effect of information acquisition**: When the three treatments are pooled, the effect of information acquisition is significantly *larger* among those with $ZeroD_i = 0$ (at a one-sided 1% level). For an individual treatment, the effect on those with $ZeroD_i = 0$ is significantly larger in all treatments (at a one-sided 5% level) except IA OwnValue.

D.4 Analyses of Student Rank-Order Lists

Finally, we investigate the effects of information provision and acquisition on individual strategies. Our theoretical basis for this analysis is contained in Appendix A.

The first information structure is *ex ante* (everyone knows the distribution of preferences but not the realization), under which we have the following hypothesis based on our theoretical results.

Hypothesis 8 (ROL: *ex ante*)**.** *A risk neutral player submits a ROL of ABC as a dominant strategy under either IA or DA.*

Result 10 (ROL: *ex ante*)**.** *More subjects play BAC instead of ABC under IA than under DA. Under IA, ABC accounts for 72% of the ROLs, followed by BAC 25%; under DA, 90% play ABC, and 8% submit BAC. The rest plays some other strategies. A session-level Wilcoxon rank-sum (or Mann-Whitney) test rejects the hypothesis that the ABC or the BAC strategy is played equally often under IA and DA (both p-values* < 0.01*).*

Note that the strategy ABC is not a dominant strategy for subjects who are sufficiently risk-averse under IA, which implies that ABC may be less played by more risk-averse subjects. On the contrary, after categorizing the subjects into two almost-equal-sized groups by risk aversion measured in the Holt-Laury lottery choice game, we find that ABC (BAC) are played by 71% (27%) of the less risk-averse subjects who switch choices before or at the 6th Holt-Laury lottery, while ABC (BAC) are played by 77% (21%) of the rest subjects who are more risk averse. This finding is consistent with Klijn et al. (2012) who also show that more risk-averse subjects are not more likely to play "safer" strategies under IA.

Recall that another information structure considered is *interim* (everyone knows her own valuation of school B and the distribution but not others' valuations). Also note that under the treatment of OwnValue, one can acquire information about her own preferences by paying some costs, which results in a game with some informed players and some uninformed. The next hypothesis is about the informed players' strategies. When testing the next hypotheses, the reported p-value is from the session-level Wilcoxon rank-sum (or Mann-Whitney) test, unless noted otherwise.

Hypothesis 9 (ROL: *interim* and Acquiring OwnValue)**.** *When a subject knows her own preferences but does not know others' preferences, it is a BNE (dominant strategy) to submit an ROL truthfully under IA (DA), regardless of the number of opponents who know their own preferences.*

Result 11 (ROL: *interim* and Acquiring OwnValue)**.** *Under IA, when the valuation of school* B *is* 10*, informed subjects are truth-telling at a similar rate –* 87% *with free information,* 88% *with costly acquired information. When the valuation of school* B *is* 110*, there are more subjects playing BAC with acquired information (*90%*) than those with free information (*85%*). However, this difference is not significant (p-value* 0.52*).*

Under DA, when the valuation of school B *is* 10*, informed subjects are truth-telling at insignificantly different rates –* 95% *with free information, 91% with costly acquired information (p-value* $= 0.87$*). When the valuation of school* B *is* 110*, however, there are significantly more subjects playing BAC with acquired information (95%) than with free information (*79%*) (p-value* $= 0.01$*).*

Lastly, we consider information structure *ex post* (valuations of school B are common knowledge) as a result of information provision and also the OtherValue treatment. Our theoretical prediction regarding the ROL is summarized below.

Hypothesis 10 (ROL: *ex post* and Acquiring OtherValue)**.** *When a subject knows both her own preferences and the preferences of her two opponents, it is a dominant strategy to rank the schools truthfully under DA; the optimal strategy under IA for low-B-valuation subjects report truthfully, while that for high-B-valuation subjects depends on the preference profile as well as the number of informed players.*

Result 12 (ROL: *ex post* and Acquiring OtherValue)**.** *Under DA, when the valuation of school* B *is* 10*, informed subjects are truth-telling at insignificantly different rates –* 92% *with free information,* 84% *with costly acquired information (p-value* $= 0.29$*). When the valuation of school* B *is* 110*, there are fewer subjects playing BAC with acquired information (*75%*) than with free information (*91%*). The difference is again insignificant (p-value =* 0.86*), partly because there are only 16 subjects who successfully acquire information.*

Under IA, when the valuation of school B *is* 10*, informed subjects are truth-telling at a similar rate — 86% with free information,* 84% *with costly acquired information. When the valuation of school* B *is* 110*, there are insignificantly more subjects playing BAC with acquired information (*85%*) than that with free information (*81%*) (p-value* $= 0.75$*).*[23]

We consider our above results to be consistent with the theoretical predictions. Furthermore, the only case where costly acquired information and freely provided information have significant effects is that when acquired information about OwnValue is associated with subjects more likely to play the dominant strategy.

Lastly, the design of our experiment enables us to investigate whether information on OtherValue affects the rate of dominant strategy play, i.e., truth-telling, in a strategy-proof mechanism, when that information is exogenously provided versus endogenously acquired.

We first study truth-telling rates when subjects, already knowing their OwnValue, are additionally provided OtherValue in the DA OtherValue treatment. This analysis enables us to compare our results with those of (Pais and Pintér 2008, Pais et al. 2011) who impose each information condition exogenously.

There are in total 108 subjects played DA OtherValue with free information in 9 sessions, each playing 10 rounds. In each round, subjects submit an ROL with information on OtherValue and another without that information. We can therefore conduct a paired t-test. To take into account that subjects may have correlated behaviors in the same session, we calculate session averages. This gives us two statistics per session: the truth-telling rate with information on OtherValue, 0.92 (s.e. = 0.02), and the truth-telling rate without this information, 0.91 (s.e. = 0.02). The difference is 0.01 (s.e. = 0.01; p-value $>$ 0.28).

[23] One may be tempted to investigate subjects' strategies conditional on the preference profile of all subjects. This however makes the samples very small, especially among those who successfully acquire information (61 in total).

We then investigate truth-telling rates when subjects, already knowing their OwnValue, have the option to acquire OtherValue in the DA OtherValue treatment (regardless of their acquisition status). There are 72 subjects in the DA OtherValue treatment in 6 session, each playing 10 rounds. Again, we calculate session averages. This gives us two statistics per session: the truth-telling rate with the option of acquiring information on OtherValue (regardless of acquisition results), 0.92 (s.e. = 0.02), and the truth-telling rate without the possibility of acquiring this information, 0.92 (s.e. = 0.01). The difference is 0.003 (s.e. = 0.01; p-value > 0.74).

Next, we conduct two sets of tests to see if the truth-telling rate is correlated with whether or not a subject successfully acquires OtherValue: i) t-tests without controlling for potential correlations across game plays (Table D.9), and ii) regression analyses (Table D.10).

Table D.9: Truth-telling Rates by Information Acquisition Status in DA OtherValue

Acquired Info?	Obs	Mean	Std. Err.	Std. Dev.
Panel A: All 720 game plays (72 subjects $\times$ 10 rounds)				
No	616	0.937	0.010	0.244
Yes	104	0.827	0.037	0.380
Difference		0.110	0.039	
Testing difference = 0:	p-value = 0.005			
Panel B: Among the 362 game plays with $WTP > 0$				
No	258	0.872	0.021	0.335
Yes	104	0.827	0.037	0.380
Difference		0.045	0.043	
Testing difference = 0:	p-value = 0.292			

Panel A of Table D.9 shows the comparison between the two groups. In terms of optimal game play (or truth-telling), the difference between them is 0.110, which is significant at the 1% level under the assumption that game plays are not correlated. The regression in column (1) of Table D.10 does the same test in a linear probability model, allowing game plays to be correlated. Again, the difference in optimal play is significant, although at the 5% level. These results seem to imply that those who acquired information on OtherValue are less likely to play DA optimally.

However, we conjecture that this significant difference is due to the fact that a lot of subjects have a zero WTP and thus optimally have never acquired information. Taking advantage of the fact that conditional on a positive WTP, a subject may be randomly denied the information, we then compare the two groups in a restricted subsample. Panel B of Table D.9 shows the results among subjects' game plays with a positive WTP. In terms of truth-telling rate, the difference between the two groups is now reduced to 0.045 and statistically insignificant.

Similarly, we can control for WTP in the regression analysis. Column (2) of Table D.10 confirms our conjecture: the coefficient on "Successfully acquired info on OtherValue" is not significant, while the one on WTP is significantly negative, implying those with a higher WTP playing sub-optimally more often. Column (3) adds more controls, and again does not show any difference between those having acquired info and others, conditional on WTP and other variables.

Table D.10: Linear Probability Model of Truth-telling (Optimal Play) with Costly Information Acquisition in DA OtherValue

	(1)	(2)	(3)
Successfully acquired info on OtherValue	-0.1098**	-0.0056	-0.0066
	(0.048)	(0.058)	(0.058)
WTP for info		-0.0201**	-0.0131
		(0.008)	(0.010)
WTP for info = 0			0.0750
			(0.052)
Round			-0.0045
			(0.004)
Free-Costly			0.0495
			(0.038)
Constant	0.9367***	0.9661***	0.9138***
	(0.019)	(0.015)	(0.063)
N	720	720	720
R^2	0.020	0.057	0.075

Notes: The dependent variable is an indicator that equals one if a subject plays truth-telling and zero otherwise. Standard errors clustered at the subject level are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix E Welfare Analysis

This appendix provides additional analyses of the welfare effects of both information provision by an educational authority and information acquisition by subjects. Section E.1 and E.2 provide some additional results, and Section E.3 evaluate the welfare effect of various information provision policies that an educational authority may adopt.

E.1 Welfare Effects of Information Provision

Free information provision changes a structure from *ex ante* to *interim* or *interim* to *ex post*. Table E.1 reports the means and standard deviations (in parentheses) of subject payoffs and the fraction of efficient allocations by information structure. Columns (1) and (3) in Table E.1 report the observed payoff and proportion of efficient allocations under each information structure, respectively. P-values for the Wilcoxon matched-pairs signed-ranks tests or the Wilcoxon rank-sum (or Mann-Whitney) tests are presented, treating each session as an independent observation.

These results complement those in Table 7 in the main text.

E.2 Welfare Effects of Information Acquisition

We now turn to the effects of costly information acquisition on welfare. As the information acquisition technology results in an endogenous probability of receiving the "hard news," there are likely both informed and uninformed subjects. If costs are not considered, we expect outcomes to fall between no information and free information provision.

Regarding the effects of information acquisition, if costs are not taken into account, we expect outcomes to fall between no information and free information provision. This is because the information acquisition technology results in an endogenous probability of receiving the "hard news," with both informed and uninformed subjects.

Table E.2 reports the means and standard deviations (in parentheses) of subject payoffs, the fraction of efficient allocations by information structure, the fraction of having successfully acquired information, the WTP for information, and the costs of information acquisition. Similar to our earlier analyses, for each treatment, we focus on the same subjects who play a pair of the school choice games in both the no-information and the costly-information scenarios in each round, where the order of the two scenarios is randomized in each round. This design feature enables us to perform both within- and between-treatment tests. the acquisition of information about OwnValue, IA achieves 89% of maximum payoffs and efficient allocations among 83% of all games; as a comparison, DA achieves 80% of maximum payoffs and efficient allocations among 73% of all games. Similarly, with the acquisition of information about OtherValue, IA achieves 97% of maximum payoffs and 96% efficient allocations, whereas DA achieves only 87% and 82%, respectively.

Table E.2 presents the fraction of times each subject successfully acquires the information as well as her expressed WTP. These are positively correlated with each other due to our experimental design. In the IA OwnValue treatment, we find that 44% of subjects obtain the desired information in each round, which is exactly the ratio of the average WTP (6.56) to the upper bound of WTP

Table E.1: Effects of Information Provision on Payoffs and Allocation Efficiency

	Payoff		Fraction(Efficient Allocation)	
	Observed in Experiment	Theoretical Prediction	Observed in Experiment	Theoretical Prediction
Information Structure	(1)	(2)	(3)	(4)
A: IA OwnValue (# obs.:720)				
Ex ante	42.51	43.33	0.69	0.68
	(51.12)		(0.49)	
Interim	50.67	52.93	0.94	1.00
	(52.52)		(0.29)	
Test: H_0: *ex ante* = *interim*; H_1: *ex ante* < *interim*				
p-value	0.01		0.01	
B: IA OtherValue (# obs.: 720)				
Interim	49.13	52.93	0.89	1.00
	(51.90)		(0.35)	
Ex post	49.12	52.93	0.91	1.00
	(52.20)		(0.34)	
Test: H_0: *interim* = *ex post*; H_1: *interim* ≠ *ex post*				
p-value	0.92		0.35	
C: DA OwnValue (# obs.: 720)				
Ex ante	42.96	43.33	0.71	0.68
	(48.93)		(0.48)	
Interim	47.22	48.67	0.84	0.87
	(54.92)		(0.43)	
Test: H_0: *ex ante* =*interim*; H_1: *ex ante*<*interim*				
p-value	0.04		0.04	
D: DA OtherValue (# obs.: 1080)				
Interim	45.90	48.67	0.81	0.87
	(49.96)		(0.39)	
Ex post	46.09	48.67	0.81	0.87
	(49.53)		(0.40)	
Test: H_0: *interim* = *ex post*; H_1: *interim* ≠ *ex post*				
p-value	0.86		0.86	
E: Comparison between IA & DA				
Test: H_0: (IA *ex ante*) = (DA *ex ante*); H_1:(IA *ex ante*) ≠ (DA *ex ante*)				
p-value	1.00		1.00	
Test: H_0: (IA *interim*) = (DA *interim*); H_1:(IA *interim*)> (DA *interim*)				
p-value: OwnValue[a]	0.01		0.01	
p-value: OtherValue[a]	0.02		0.02	
Test: H_0: (IA *ex post*) = (DA *ex post*); H_1:(IA *ex post*) > (DA *ex post*)				
p-value	0.02		0.01	

Notes: This table reports the means and standard deviations (in parentheses) of payoffs and the fraction of efficient allocations by information structure. It only uses data from the rounds with free information provision and the corresponding no information setting. Also presented are p-values for the Wilcoxon matched-pairs signed-ranks tests or the Wilcoxon rank-sum (or Mann-Whitney) tests. All tests are performed with the session averages of payoffs or efficiency. All data are weighted at the session level so that the probability of having a high valuation for school B equals $1/5$.

a. These two p-values are calculated with the samples of IA and DA OwnValue treatments and the one with OtherValue treatments, respectively.

Table E.2: Effects of Information Acquisition on Payoffs and Allocation Efficiency

	Payoff[a]	Fraction(Efficient Allocation)	Pr(Info Acquired)	WTP	Costs Paid[b]
		A: IA OwnValue (# obs.: 720)			
Ex ante	42.50	0.69			
	(51.00)	(0.54)			
Acquiring OwnValue	47.05	0.83	0.44	6.56	2.25
	(52.77)	(0.47)	(0.50)	(4.78)	(3.56)
Test: H_0: *ex ante* = (Acquiring OwnValue); H_1: *ex ante* $<$ (Acquiring OwnValue)					
p-value	0.01	0.01			
		B: IA OtherValue (# obs.:720)			
Interim: Privately Informed	49.98	0.92			
	(56.75)	(0.42)			
Acquiring OtherValue	51.36	0.96	0.28	4.49	1.29
	(54.07)	(0.35)	(0.45)	(4.56)	(2.66)
Test: H_0: *interim* = (Acquiring OtherValue); H_1: *Interim* $\neq$ (Acquiring OtherValue)					
p-value	0.25	0.25			
		C: DA OwnValue (# obs.: 720)			
Ex ante	42.73	0.70			
	(52.73)	(0.51)			
Acquiring OwnValue	43.80	0.73	0.30	4.44	1.35
	(48.73)	(0.49)	(0.46)	(4.38)	(2.88)
Test: H_0: *ex ante* = (Acquiring OwnValue); H_1: *ex ante* $<$ (Acquiring OwnValue)					
p-value	0.06	0.06			
		D: DA OtherValue (# obs.: 720)			
Interim: Privately Informed	46.77	0.82			
	(50.46)	(0.43)			
Acquiring OtherValue	46.27	0.82	0.14	2.21	0.48
	(52.46)	(0.45)	(0.35)	(3.15)	(1.50)
Test: H_0: *interim* = (Acquiring OtherValue); H_1: *Interim* $\neq$ (Acquiring OtherValue)					
p-value	0.92	0.92			
		E: Comparison between IA & DA			
Test: H_0: (IA Acquiring OwnValue) = (DA Acquiring OwnValue) H_1: (IA Acquiring OwnValue) $>$ (DA Acquiring OwnValue)					
p-value	0.00	0.00			
Test: H_0: (IA Acquiring OtherValue) = (DA Acquiring OtherValue) H_1: (IA Acquiring OtherValue) $>$ (DA Acquiring OtherValue)					
p-value	0.00	0.00			

Notes: This table reports the means and standard deviations (in parentheses) of payoffs and the fraction of efficient allocations by information structure. It only uses data from the rounds with costly information acquisition and the corresponding no information setting. This table presents p-values for the Wilcoxon matched-pairs signed-ranks tests and Wilcoxon rank-sum (or Mann–Whitney) tests. All data are weighted at the session level so that the probability of having high valuations of school B equals $1/5$. All tests are performed with the session averages of payoffs or efficiency.

a. "Payoff" does not take into account the cost of information acquisition paid in the experiment.

b. "Costs paid" measures the actual costs subjects paid in the experiment.

(15). By contrast, we find that subjects acquire the information less often in the other treatments, ranging from 14% in the DA OtherValue treatment to 30% in the DA OwnValue treatment.

To evaluate the net effects of information acquisition, it is necessary to consider the costs. Section 5.4 in the main text, especially Table 7, provides more details on the welfare implications of these costs.

Table E.3: Welfare Effects of Counterfactual Policies (Relative to *ex ante*)

	Laissez-Faire Policy Costly Info Acquisition		*Counterfactual 1* Free OwnValue, Costly OtherValue		*Counterfactual 2* Free OwnValue
	w/ low cost[a]	w/ high cost[a]	w/ low cost[a]	w/ high cost[a]	& Free OtherValue
IA	2.34	-0.12	8.26	6.93	8.15
DA	-0.57	-2.00	3.99	2.69	4.68

Notes: This table presents the welfare effects of information acquisition and information provision relative to *ex ante* (i.e., everyone knows the distribution, but nobody knows her own or others' preferences).
a. "Low cost" and "high cost" are two technologies for information acquisition. The former is the one used in the experiment, where a subject in expectation pays a half of her WTP when successfully acquiring the information; in the latter, the subject always pays her WTP if successfully acquiring information. Otherwise, subjects do not pay.

E.3 Designing Information-Provision Policies: Counterfactual Analyses

Using the above results, we can now evaluate the welfare effect of various information provision policies. More specifically, we focus on the following three types of policies, measuring welfare relative to the *ex ante* baseline where everyone knows the distribution but no one knows her own or others' preferences:

(i) **Laissez-Faire Policy**: The educational authority provides no information but lets students acquire information as they wish with either the low- or high-cost technology.

(ii) **Counterfactual 1: Free OwnValue and Costly OtherValue**: The educational authority makes all information relevant to OwnValue available but does not provide information about OtherValue. This policy corresponds to those employed by many school districts where information about school characteristics is readily available, but information about others' actions is not. In this setting, students may rely on historical data to infer others' actions for the current year.

(iii) **Counterfactual 2: Free OwnValue and Free OtherValue**: The educational authority makes all relevant information freely available.

With the estimated effects of information acquisition and provision, we can now calculate the welfare, measured by the student average payoff in each round, created by each policy. Our results are summarized in Table E.3. Taking the free-OwnValue-free-OtherValue policy as an example, we see that its welfare effect under IA is the sum of the welfare gain from providing OwnValue (8.16) and that from providing OtherValue (-0.01) as shown in Table 7.

To analyze the welfare effects under the laissez-faire policy, some additional assumptions are needed. For instance, under IA, we first take the net payoff gain of having OwnValue acquisition under the low-cost assumption (2.29 in Table 7). We then designate that only those who have successfully acquired OwnValue can engage in acquiring OtherValue. This comprises about 44% of our subjects. We further assume that this leads to 44% of the net payoff gain from acquiring OtherValue ($0.10 \times 44\%$ as in Table 7).[24] Similarly, for the free-OwnValue-costly-OtherValue policy, we take into account the effect of providing OwnValue as well as that of letting subjects acquire OtherValue (given that they know OwnValue already).

[24]Note that we ignore the fact that the game with this two-stage information acquisition will have both informed and uninformed players regarding their own values.

Overall, making both OwnValue and OtherValue freely available leads to an additional 8.15 (4.68) points for every subject in each round under IA (DA). When the cost is low, the laissez-faire policy increases average payoffs only under IA. When the cost is high, this benefit disappears; in other words, engaging in information acquisition decreases social welfare, on average. In comparison, when the cost is high, the free-OwnValue-costly-OtherValue policy is always welfare-improving relative to *ex ante*, but is dominated by the free-OwnValue-free-OtherValue policy.

Interestingly, the comparison between Counterfactuals 1 and 2 reveals that there is always a welfare gain for providing free information about others' preferences under DA. Theoretically, information about others' preferences should affect neither strategies nor outcomes under DA. However, given our observed over-investment in information acquisition, we can interpret the free provision of information as an intervention to reduce wasteful investment. This result has policy implications for school districts using DA, suggesting that educational authorities should actively provide information about others' preferences/actions even under DA.