

# Information Acquisition and Provision in School Choice\*

Yan Chen

Yinghua He

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## Abstract

When participating in school choice, students who want to know perfectly their preferences over schools face information acquisition costs. In this study, we examine how two popular school choice mechanisms, the (Boston) Immediate Acceptance and the Deferred Acceptance, incentivize students' information acquisition. Specifically, we show that only the Immediate Acceptance mechanism incentivizes students to learn their own cardinal and others' preferences. We also show the welfare effects of various policies of information provision. Furthermore, we find that, while a lab experiment yields results consistent with the theoretical predictions, students systematically over-pay for information, especially when they believe that others spend generously. We use these results to suggest that it is welfare-enhancing if education authorities provide more information to help each participant learn both her own and others' preferences. Doing so improves match efficiency while reducing the (socially wasteful) costs of information acquisition.

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

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# 1 Introduction

“It was very hard, and very time-consuming,” New Orleans resident Carrie Fisher 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*.

When choosing a school, students often have imperfect information on their own preferences over candidate schools, partly because it is difficult to assess the potential educational outcomes for each school (Dustan, de Janvry and Sadoulet 2015). However, acquiring this information can be costly if a student faces too many choices, or must acquire information on a number of factors, such as academic performance, teacher quality, school facilities, extra-curricular activities offered, and peer quality. As a result, a student may just choose the same or a similar school as her older sibling whose school was (partially) a random outcome (Dustan 2015).

The cost of information acquisition is especially significant for low-income students. Indeed, research has shown that low-income high achievers in the U.S. tend not to apply to selective colleges, in spite of the fact that attending those institutions would cost less than the ones the students do attend thanks to generous financial aid, due to limited information (Hoxby and Avery 2013, Hoxby and Turner 2015). Informational intervention can therefore substantially raise their applications to selective colleges (Hoxby and Turner 2013). Similar effects are also observed among low-income families in public school choice plans (Hastings and Weinstein 2008).

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

Specifically, in a school choice setting with unknown preferences and costly information acqui-

sition, we show that both the strategy-proof DA and the non-strategy-proof IA incentivize students to acquire information on their own ordinal preferences. However, we find that only the non-strategy-proof mechanism induces students to learn their own cardinal preferences with which the IA mechanism can sometimes be more efficient than the DA mechanism (Abdulkadiroğlu, Che and Yasuda 2011). The lack of strategy-proofness in the IA mechanism also implies that information on others' preferences can be useful for the purpose of competing with other students. As such, the acquisition of information on others' preferences is more likely to be individually rational but socially wasteful, a disadvantage of a non-strategy-proof mechanism.

In addition to studying the incentive to acquire preference information, we investigate the welfare effects of information provision by education authorities. In a setting where students have the same ordinal preferences, we find that the *ex ante* welfare is constant under the DA mechanism across information structures, while providing information on one's own cardinal preferences improves welfare under the IA mechanism. However, we find that provision of information on others' preferences has ambiguous effects.

To search for behavioral regularities and to quantify the welfare effects of information acquisition and provision, we use a laboratory experiment. Specifically, we use the Becker-DeGroot-Marschak mechanism to elicit willingness-to-pay (WTP) for information (Becker, DeGroot and Marschak 1964). Our experimental results show that students' WTP for their own and others' preferences under the non-strategy-proof IA mechanism is significantly greater than it is under the strategy-proof DA mechanism. These results are consistent with our theoretical predictions. However, we find that their WTP is systematically higher than the theoretical prediction. We thus decompose this excess WTP and find that both conformity and curiosity explain the over-investment in information acquisition. That is, a student tends to have a high WTP when she expects a high WTP by others and when she has a high WTP for non-instrumental information.

To provide guidance for designing school choice, we study the welfare effects of three policies of information provision. The first is a laissez-faire policy in which the educational authority does not interfere with students' information acquisition. Our experimental results show that, relative to the case without information acquisition, this policy is always welfare-decreasing under the DA mechanism and can be welfare-improving under the IA mechanism if the cost of information acquisition is very low.

The second is a policy to freely provide information on a student's own cardinal preferences but to let students acquire information on others' preferences at a cost. Consistent with our theoretical prediction, evidence shows that, compared to the laissez-faire policy, this one achieves higher welfare under either mechanisms, more so under IA.

The third is a policy that offers free information on both a student's own and others' preferences. Our findings imply no difference between the second and third policies in terms of average welfare if we do not consider the costs of information acquisition. However, due to the excessive WTP we observe, the free information on others' preferences improves welfare by saving students from paying wasteful costs. This result may be expected under the non-strategy-proof IA mechanism, but not under the strategy-proof DA mechanism. On the contrary, we show that the third policy results in an even higher welfare gain under the DA than under the IA mechanism.

Together, our findings imply that the school districts using either DA or IA can improve student welfare by providing information on both a student's own and others' preferences. The information on a student's own preferences might be provided through presentation materials on schools (Hastings and Weinstein 2008) or by targeting disadvantaged population (Hoxby and Turner 2015). The information on others' preferences might be provided by publishing applicants' strategies and allowing students to revise their applications upon observing others' strategies (De Haan, Gautier, Oosterbeek and Van der Klaauw 2015, Dur, Hammond and Morrill 2015).

## **2 Literature Review**

This study contributes to the matching literature. Typically, these studies assume that agents know their preferences (Gale and Shapley 1962, Roth and Sotomayor 1990, Abdulkadiroğlu and Sönmez 2003). One exception is Chade, Lewis and Smith (2014), who consider the case where colleges observe signals of students' ability but do not have the possibility to acquire information. Allowing this possibility, Lee and Schwarz (2012) and Rastegari, Condon and Immorlica (2013) study settings where firm preferences over workers are not completely known and are revealed only through interviews.

To our knowledge, the only theoretical papers that address endogenous information acquisition in matching are those of Bade (2015) and Harless and Manjunath (2015). In the context of house

allocations, Bade finds that the unique *ex ante* Pareto optimal, strategy-proof and non-bossy allocation mechanism is that of serial dictatorship. However, in their study, Harless and Manjunath (2015) prove that the top-trading-cycles mechanism dominates the serial dictatorship mechanism under progressive measures of social welfare. Both papers focus on ordinal mechanisms. As we show below, in any strategy-proof ordinal mechanism, students have no incentives to learn their cardinal preferences, while information on cardinal preferences can be welfare-improving, especially when students have similar ordinal preferences (Abdulkadiroğlu et al. 2011). Lastly, in an ongoing study, Artemov (2016) considers an environment similar to our experimental setting to compare the performance of the IA and DA mechanisms.

Another unique feature of our study is the acquisition of information on others' preferences, which is in contrast with other studies that focus on the acquisition of information on one's own preferences. One exception in this body of literature is Kim (2008), who considers a common-value first-price auction with two bidders, one of whom learns her opponent's signal.

In addition to the matching literature, information acquisition is considered in other fields, e.g., bargaining (Dang 2008), committee decisions (Persico 2004, Gerardi and Yariv 2008), contract theory (Crémer, Khalil and Rochet 1998, Crémer and Khalil 1992), 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 theoretical literature on the role of information acquisition in mechanism design, especially in auction design, e.g., Persico (2000), Compte and Jehiel (2007), Crémer, Spiegel and Zheng (2009), Shi (2012), surveyed in Bergemann and Valimaki (2006). Notably, Bergemann and Valimaki (2002) show that the Vickrey-Clark-Groves mechanism guarantees both *ex ante* and *ex post* efficiency in every private value environment.

While the literature on information acquisition is mostly theoretical, there are a few experimental investigations in various contexts. For example, Gabaix, Laibson, Moloche and Weinberg (2006) use two experiments with costly information acquisition to test the directed cognition model against the fully rational model. In another setting, 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. Finally, Bhattacharya, Duffy and Kim (2015) study endogenous information acquisition in voting.

In comparison, the experimental school choice literature has focused on strategy, stability and welfare comparisons among various mechanisms assuming that students know their own preferences (Chen and Sönmez 2006, Featherstone and Niederle 2008, Calsamiglia, Haeringer and Klijn 2010, Klijn, Pais and Vorsatz 2012). In addition, while Pais and Pintér (2008) and Pais, Pintér and Veszteg (2011) study matching mechanisms in different information settings, they treat the information setting as exogenous. Therefore, their results focus more on the robustness of the mechanisms to information. More recently, several experimental studies of school choice have examined peer information sharing within networks (Ding and Schotter 2015b) as well as inter-generational (Ding and Schotter 2015a) and top-down advice (Guillen and Hing 2014). Our paper contributes to the experimental literature by providing the first experimental evidence on information acquisition in the school choice context.

### 3 Theoretical Analysis

In this section, we outline a theoretical model of endogenous information acquisition for one’s own and others’ preferences under two common school choice mechanisms, the Immediate and Deferred Acceptance mechanisms.

#### 3.1 The Setup

Our model begins with a finite set of students,  $I$ , to be assigned to a finite set of schools,  $S$ , through a centralized school choice mechanism.  $S$  contains a “null school” or outside option,  $s^0$ , that denotes the possibility of not being matched with any school in  $S \setminus \{s^0\}$ . For each  $s \in S$ , there is a finite supply of seats,  $q_s \in \mathbb{N}$ , but enough seats to accommodate all students,  $\sum_{s \in S \setminus \{s^0\}} q_s = |I|$ , while  $q_{s^0} > 0$  for all  $s$ . By assumption,  $q_{s^0} \geq |I|$ . Following Abdulkadiroğlu et al. (2011), we assume that schools rank students using a common and even lottery (single tie-breaking) whose realization is unknown to students when they enter the mechanism.

For each student  $i \in I$ , her valuations of schools are i.i.d. draws from a distribution,  $F$ , denoted by a vector  $V_i = [v_{i,s}]_{s \in S}$ , where  $v_{i,s} \in [0, 1]$  is  $i$ ’s von Neumann-Morgenstern utility associated with school  $s$ .

To simplify notation, we assume that student preferences are strict: For any pair of distinct

schools  $s$  and  $t$ ,  $v_{i,s} \neq v_{i,t}$  for all  $i$ . Furthermore, we 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 distribution of  $P$  implied by  $F$  is  $G(P|F)$ . We impose a full-support assumption on  $G(P|F)$ , i.e.,  $G(P|F) > 0, \forall P \in \mathcal{P}$ , whereas  $G(P^\phi|F) = 0$ , indicating that every strict ordinal preference ranking is possible given the distribution of cardinal preferences.

In our model, 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.

### 3.2 School Choice Mechanisms

To model information acquisition in the school choice context, we focus on two mechanisms popular in both research literature and practice: the Immediate-Acceptance mechanism (also known as the Boston mechanism) and the Gale-Shapley Deferred-Acceptance mechanism.

The **Immediate-Acceptance** 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 ranking over students and consists of the following rounds:

*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  $k$ th 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  $k$ th 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.

The **Gale-Shapley Deferred-Acceptance** mechanism (DA) can be either student-proposing or school-proposing. We focus on the student-proposing DA mechanism in this study. Specifically,

the mechanism collects school capacities and students' ROLs for schools. With strict rankings of schools over students that are determined by pre-specified rules, it 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  $k^{th}$  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. Those who are not rejected are temporarily held.

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

### 3.3 Acquiring Information on Own Preferences

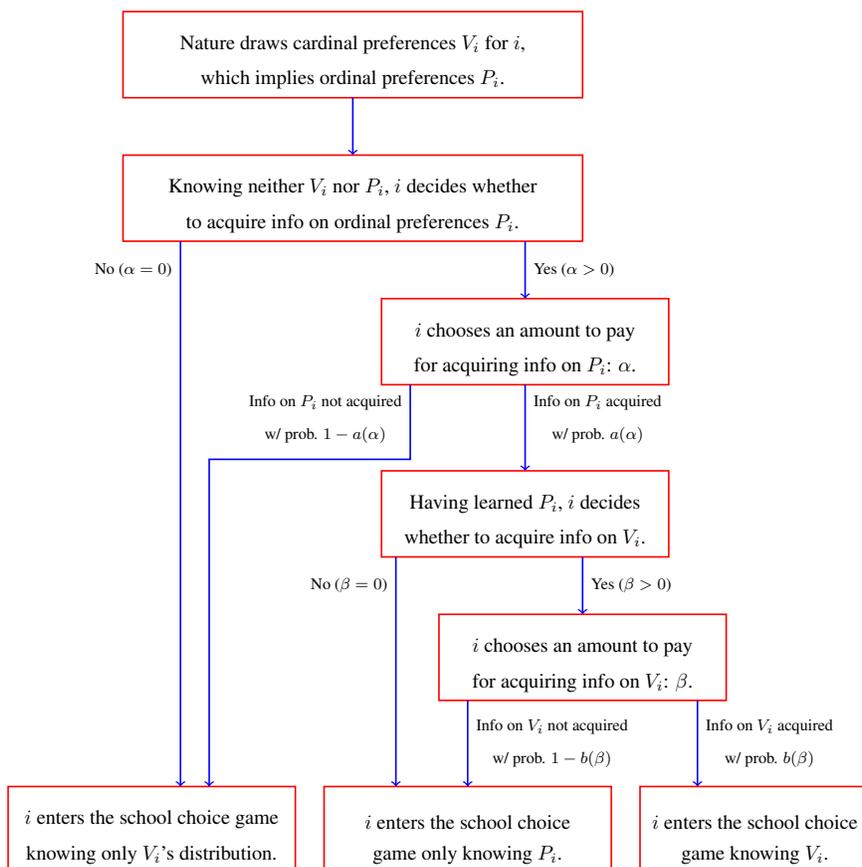


Figure 1: Acquiring Information on One's Own Preferences.

We first investigate the incentives to acquire information on one's own value. The timing of the game and the corresponding information structure are described as follows and also in Figure 1:

- (i) Nature draws individual valuation  $V_i$ , and thus ordinal preferences  $P_i$ , from  $F(V)$  for each  $i$ , but  $i$  knows only the value distribution  $F(V)$ ;
- (ii) Each individual  $i$  decides whether to acquire a signal on her ordinal preferences; If yes, she decides how much to invest in information acquisition, denoted by  $\alpha \in [0, \bar{\alpha}]$ .
- (iii) If ordinal preferences are learned, she then chooses the investment,  $\beta \in [0, \bar{\beta}]$ , to acquire a signal on her cardinal preferences.
- (iv) Regardless of the information acquisition decision or outcome, every student plays the school choice game under either IA or DA.

### 3.3.1 Technology of Information Acquisition

Information acquisition in our model is covert. That is,  $i$  knows that others are engaging in information acquisition, but does not know what information they have acquired.

The information acquisition process consists of two stages (see Figure 1):  $i$  first pays a cost  $\alpha$  to acquire a signal on the ordinal preference,  $\omega_{1,i} \in \bar{\mathcal{P}}$ . With probability  $a(\alpha)$ , she learns perfectly,  $\omega_{1,i} = P_i$ ; by contrast, with probability  $1 - a(\alpha)$  she learns nothing,  $\omega_{1,i} = P^\phi$ . In the second stage, having learned ordinal preferences  $P_i$ ,  $i$  may pay another cost,  $\beta$ , to learn her cardinal preferences by acquiring a signal  $\omega_{2,i} \in \bar{\mathcal{V}}$ , where  $\bar{\mathcal{V}} \equiv \mathcal{V} \cup \emptyset \equiv \bar{\mathcal{V}} \cup \emptyset$ . Here, with probability  $b(\beta)$ , she learns her cardinal preferences,  $\omega_{2,i} = V_i$ ; by contrast, with probability  $1 - b(\beta)$ , she learns nothing,  $\omega_{2,i} = V^\phi$ , where  $V^\phi \equiv \emptyset$  denotes no cardinal preference information.

The technologies  $a(\alpha)$  and  $b(\beta)$  are such that  $a(0) = b(0) = 0$ ,  $\lim_{\alpha \rightarrow \infty} a(\alpha) = \lim_{\beta \rightarrow \infty} b(\beta) = 1$ ,  $a', b' > 0$ ,  $a'', b'' < 0$ , and  $a'(0) = b'(0) = +\infty$ .<sup>1</sup> The cost of information acquisition is  $c(\alpha, \beta)$ , where  $c(0, 0) = 0$ ,  $c_\alpha, c_\beta, c_{\alpha\beta}, c_{\alpha\alpha}, c_{\beta\beta} > 0$  for all  $(\alpha, \beta)$  and  $c_\alpha(0, 0), c_\beta(\alpha, 0) < +\infty$  for all  $\alpha > 0$ . Given these restrictions, we limit our attention to  $\alpha \in [0, \bar{\alpha}]$  and  $\beta \in [0, \bar{\beta}]$ , where  $c(\bar{\alpha}, 0) = c(0, \bar{\beta}) = 1$ , so that  $c(\alpha, \beta)$  does not exceed the maximum possible payoff (=1).

<sup>1</sup>The infinite marginal productivity at zero input is consistent with, for example, the Cobb-Douglas function. When necessary, we define  $0 \cdot \infty = 0$ .

After the two-stage information acquisition,  $i$  observes signals  $\omega_i = (\omega_{1,i}, \omega_{2,i}) \in \bar{\mathcal{P}} \times \bar{\mathcal{V}}$ . If  $i$  pays  $(\alpha, \beta)$ , the distribution of signals is  $H(\omega_i | \alpha, \beta)$ , as outlined below:

$$\begin{aligned} H(\omega_i = (P^\phi, V^\phi) | \alpha, \beta) &= 1 - a(\alpha), \\ H(\omega_i = (P_i, V^\phi) | \alpha, \beta) &= a(\alpha)(1 - b(\beta)), \\ H(\omega_i = (P_i, V_i) | \alpha, \beta) &= a(\alpha)b(\beta), \\ H(\omega_i = (P, V) | \alpha, \beta) &= 0 \text{ if } (P, V) \notin \{(P^\phi, V^\phi), (P_i, V^\phi), (P_i, V_i)\}. \end{aligned}$$

Upon observing signal  $\omega_i$ , the posterior distributions of cardinal and ordinal preferences are:

$$F(V | \omega_i) = \begin{cases} F(V) & \text{if } \omega_i = (P^\phi, V^\phi), \\ F(V | P_i) & \text{if } \omega_i = (P_i, V^\phi), \\ 1_{V_i} & \text{if } \omega_i = (P_i, V_i); \end{cases} \quad G(P | \omega_i) = \begin{cases} G(P | F) & \text{if } \omega_i = (P^\phi, V^\phi), \\ 1_{P_i} & \text{if } \omega_i = (P_i, V^\phi), \\ 1_{P_i} & \text{if } \omega_i = (P_i, V_i); \end{cases}$$

where  $1_{V_i}$  (or  $1_{P_i}$ ) is the probability distribution placing probability 1 on point  $V_i$  (or  $P_i$ ).

### 3.3.2 Game of School Choice with Information Acquisition

In our model, after observing the signal  $\omega_i$ , students enter the school choice game under either DA or IA. Each student  $i$  submits an ROL denoted by  $L_i \in \mathcal{P}$  such that  $sL_it$  if and only if  $s$  is ranked above  $t$ .<sup>2</sup> When  $i$  submits  $L_i$  and others submit  $L_{-i}$ , the payoff is represented by:

$$u(V_i, L_i, L_{-i}) = \sum_{s \in S} a_s(L_i, L_{-i}) v_{i,s} \equiv A(L_i, L_{-i}) \cdot V_i,$$

where  $a_s(L_i, L_{-i})$  is the probability that  $i$  is accepted by  $s$ , given  $(L_i, L_{-i})$ , and  $A(L_i, L_{-i})$  is the vector of the probabilities determined by the mechanism. We further distinguish between two types of mechanisms: strategy-proof and non-strategy-proof. A mechanism is **strategy-proof** if:

$$u(V_i, P_i, L_{-i}) \geq u(V_i, L_i, L_{-i}), \forall L_i, L_{-i}, \text{ and } \forall V_i;$$

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<sup>2</sup>We restrict the set of actions to the set of possible ordinal preferences,  $\mathcal{P}$ . In other words, students are required to rank all schools in  $S$  including  $s^0$ , which differs from reality where the outside option is not included in ROL. However, we assume that  $i$  is always assigned to  $s^0$  when she is rejected by all  $s$  s.t.  $sL_i s^0$ . Thus, the effective ROL is truncated at  $s^0$ , which makes our restriction of  $L_i \in \mathcal{P}$  innocuous.

i.e., reporting true ordinal preferences is a dominant strategy. It is well-known that the student-proposing DA is strategy-proof (Dubins and Freedman 1981, Roth 1982), while IA is not (Abdulkadiroğlu and Sönmez 2003).

Under either mechanism, a **symmetric Bayesian Nash equilibrium** is defined by a tuple  $(\alpha^*, \beta^*(P, \alpha^*), \sigma^*(\omega))$  such that, for all  $i$ :

(i) A (possibly mixed) strategy  $\sigma^*(\omega) : \bar{\mathcal{P}} \times \bar{\mathcal{V}} \rightarrow \Delta(\mathcal{P})$ ,

$$\sigma^*(\omega) \in \arg \max_{\sigma} \left\{ \int \int \int u(V, \sigma, \sigma^*(\omega_{-i})) dF(V|\omega) dF(V_{-i}|\omega_{-i}) dH(\omega_{-i}|\alpha_{-i}^*, \beta_{-i}^*) \right\}.$$

That is, given one's own signal  $\omega$ , everyone best responds to others, taking into account that others have paid  $(\alpha_{-i}^*, \beta_{-i}^*)$  to acquire information. We further define the value function given  $(\omega, \alpha_{-i}^*, \beta_{-i}^*)$ :

$$\begin{aligned} & \Pi(\omega, \alpha_{-i}^*, \beta_{-i}^*) \\ &= \max_{\sigma} \left\{ \int \int \int u(V, \sigma, \sigma^*(\omega_{-i})) dF(V|\omega) dF(V_{-i}|\omega_{-i}) dH(\omega_{-i}|\alpha_{-i}^*, \beta_{-i}^*) \right\}. \end{aligned}$$

(ii) Acquisition of information on cardinal preferences  $\beta^*(P, \alpha^*) : \mathcal{P} \times [0, \bar{\alpha}] \rightarrow [0, \bar{\beta}]$ ,  $\forall P$ ,

$$\beta^*(P, \alpha^*) \in \arg \max_{\beta} \left\{ \begin{aligned} & b(\beta) \int \Pi((P, V), \alpha_{-i}^*, \beta_{-i}^*) dF(V|P) \\ & + (1 - b(\beta)) \Pi((P, V^\phi), \alpha_{-i}^*, \beta_{-i}^*) - c(\alpha^*, \beta) \end{aligned} \right\}.$$

Here,  $\beta^*(P, \alpha^*)$  is the optimal decision given that one has learned her ordinal preference ( $P$ ) after paying  $\alpha^*$  to acquire  $P$ .

(iii) Acquisition of information on ordinal preferences  $\alpha^* \in [0, \bar{\alpha}]$ ,

$$\alpha^* \in \arg \max_{\alpha} \left\{ \begin{aligned} & a(\alpha) \int \left[ \begin{aligned} & b(\beta^*(P, \alpha)) \int \Pi((P, V), \alpha_{-i}^*, \beta_{-i}^*) F(V|P) \\ & + (1 - b(\beta^*(P, \alpha))) \Pi((P, V^\phi), \alpha_{-i}^*, \beta_{-i}^*) \\ & - c(\alpha, \beta^*(P, \alpha)) \end{aligned} \right] dG(P|F) \\ & + (1 - a(\alpha)) [\Pi((P^\phi, V^\phi), \alpha_{-i}^*, \beta_{-i}^*) - c(\alpha, 0)] \end{aligned} \right\}.$$

The above expression has already taken into account that the optimal  $\beta$  equals zero if one

obtains a signal  $\omega_1 = P^\phi$  in the first stage:  $\beta^*(P^\phi, \alpha) = 0$  for all  $\alpha$ .

Given the above, we can now state our existence result in Lemma 1:

**Lemma 1.** *Under DA or IA, a symmetric Bayesian Nash equilibrium exists.*

This also leads to our first proposition:

**Proposition 1.** *In a symmetric Bayesian Nash equilibrium  $(\alpha^*, \beta^*(P, \alpha^*), \sigma^*(\omega))$  under DA or IA, we expect the following:*

- (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  $P$ .

**Remark 1.** *Similar to the results for DA, students have no incentive to learn their own cardinal preferences when a strategy-proof mechanism elicits ordinal preferences.<sup>3</sup>*

### 3.4 Acquiring Information on Others' Preferences

We now consider a student's incentive to acquire information on others' types/preferences. Here, we assume that everyone knows exactly 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 with the same properties as before. The process and technology for information acquisition are depicted in Figure 2.

To acquire information, student  $i$  may pay  $\delta$  to acquire a signal of  $V_{-i}$ ,  $\omega_{i,3} \in \bar{\mathcal{V}}^{|I|-1}$ . With probability  $d(\delta)$ , she learns others' preferences perfectly,  $\omega_{3,i} = V_{-i}$ ; with probability  $1 - d(\delta)$ ,  $\omega_{3,i} = V_{-i}^\phi \equiv \emptyset$ , i.e., she learns nothing. The distribution of signals and the posterior distribution of preferences are as follows:

$$\begin{aligned} K(\omega_{3,i} = V_{-i}^\phi | \delta) &= 1 - d(\delta), \\ K(\omega_{3,i} = V_{-i} | \delta) &= d(\delta), \\ K(\omega_{3,i} = V'_{-i} | \delta) &= 0 \text{ if } V'_{-i} \notin \{V_{-i}, V_{-i}^0\}; \end{aligned} \quad F(V_{-i} | \omega_{3,i}) = \begin{cases} F(V_{-i}) & \text{if } \omega_{3,i} = V_{-i}^\phi; \\ 1_{V_{-i}} & \text{if } \omega_{3,i} = V_{-i}. \end{cases}$$

<sup>3</sup>This statement does not extend to mechanisms that directly use information on cardinal preferences, e.g., Hylland and Zeckhauser (1979), Budish (2011), and He, Miralles, Pycia and Yan (2015)

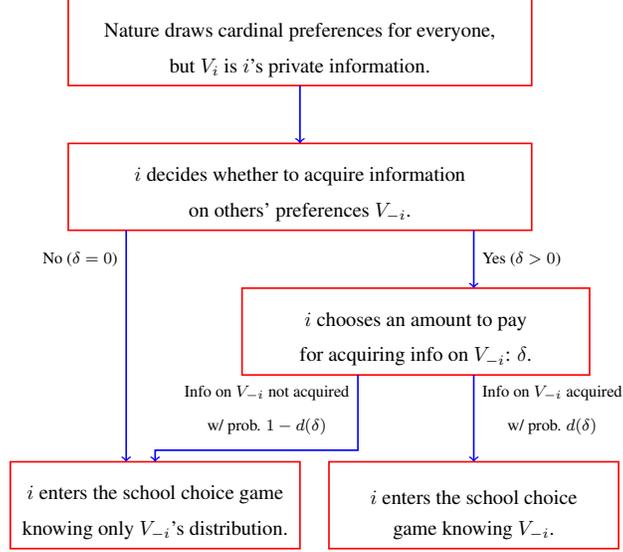


Figure 2: Acquiring Information on Others' Preferences.

The technology has the following properties:  $d(0) = 0$ ,  $\lim_{\delta \rightarrow \infty} d(\delta) = 1$ ,  $d' > 0$ ,  $d'' < 0$ , 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  $e(\bar{\delta}) = 1$ .

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  $\bar{\sigma}^*(\omega_3, V) : \bar{\mathcal{V}}^{(|I|-1)} \times \mathcal{V} \rightarrow \Delta(\mathcal{P})$ , such that

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

That is, given one's own signal  $\omega_{3,i}$ , everyone best responds to others, taking into account that they have paid  $\delta^*$  to acquire information (denoted as  $\delta_{-i}^*$ ). We further define the value function given  $(\omega_{3,i}, \delta_{-i}^*)$  and  $V_i$  as:

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

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

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

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

The existence of such an equilibrium can be proven by similar arguments in the proof of Lemma 1, and the properties of information acquisition in equilibrium is summarized as follows:

**Proposition 2.** *Suppose  $(\delta^*(V), \sigma^*(\omega_3, V))$  is a symmetric Bayesian Nash equilibrium under a given mechanism. We then expect:*

(i)  $\delta^*(V) = 0$  for all  $V$  under DA;

(ii) *There always exists a preference distribution  $F$  such that  $\delta^*(V) > 0$  under IA for  $V$  in some positive-measure set.*

**Remark 2.** *Similar to the results for DA, students have no incentive to learn others' preferences when a strategy-proof mechanism elicits either ordinal or cardinal information from students.*

In short, this result provides another perspective on strategy-proofness as a desideratum in market design: a strategy-proof mechanism makes the school choice game easier to play by reducing the incentive to acquire information on others' preferences to zero.

### 3.5 Welfare Effects of Information Provision

While students always have incentives to acquire information on their own preferences and sometimes on others' preferences, information is not always successfully acquired due to the costs. In this section, we examine the impact of information provision by education authorities.

In our model, we assume that the provision of information decreases the cost of information acquisition to zero, while the lack of it increases such cost to infinity. For simplicity, we focus on a special setting where everyone has the same ordinal (but different cardinal) preferences, similar to the setting in Abdulkadiroğlu et al. (2011) and Troyan (2012). We relax this assumption in our experiment (cf. section 4).

We start with a prior  $F$ , and thus  $G(P|F)$  such that after a  $P$  is drawn, it becomes everyone's ordinal preference. In addition, we consider every school to be acceptable:  $v_{i,s} > 0$  for all  $i$  and  $s$ . We use  $F_{v_s}$  to denote the marginal distribution of the cardinal preference for school  $s$ .

We next represent the education authority's decision regarding how much information to release by sending a vector of signals to every  $i$ :  $\bar{\omega}_i = (\bar{\omega}_{1,i}, \bar{\omega}_{2,i}, \bar{\omega}_{3,i}) \in \bar{\mathcal{P}} \times \bar{\mathcal{V}} \times \bar{\mathcal{V}}^{(|I|-1)}$ , where  $\bar{\omega}_{1,i}$

and  $\bar{\omega}_{2,i}$  are the signals of  $i$ 's ordinal and cardinal preferences respectively, and  $\bar{\omega}_{3,i}$  is the signal of others' cardinal preferences. All signals are such that  $\bar{\omega}_{1,i} \in \{P^\phi, P_i\}$ ,  $\bar{\omega}_{2,i} \in \{V^\phi, V_i\}$ , and  $\bar{\omega}_{3,i} = \{V_{-i}^\phi, V_{-i}\}$ , i.e., they are either perfectly informative or completely uninformative.

We study the *ex ante* welfare in equilibrium under each of the following information structures:

- (i) Uninformed (**UI**):  $\bar{\omega}_i = (P^\phi, V^\phi, V_{-i}^\phi), \forall i$ ;
- (ii) Ordinally Informed (**OI**):  $\bar{\omega}_i = (P_i, V^\phi, V_{-i}^\phi), \forall i$ ;
- (iii) Cardinaly Informed (**CI**):  $\bar{\omega}_i = (P_i, V_i, V_{-i}^\phi), \forall i$ ;
- (iv) Perfectly Informed (**PI**):  $\bar{\omega}_i = (P_i, V_i, V_{-i}), \forall i$ .

It should be noted that the identical ordinal preference is common knowledge under OI, CI, or PI. However, under UI, no one knows the realization of ordinal preference, but everyone knows that the ordinal preference will be the same across students.

These four information structures reflect possible outcomes of different school choice policies. When the education authority makes it difficult for students to acquire information on schools, we are likely to be in the UI scenario. When it makes some information easy to access, students may find it costless to learn their ordinal preferences, and thus we are likely in the OI scenario. If all information on own preferences is readily available, we are likely to be in the CI scenario.

We are also interested in the PI scenario, which relates to the gaming part of school choice under a non-strategy-proof mechanism. From Proposition 2, individual students have incentives to acquire information on others' preferences under IA. The literature has shown that this additional strategic behavior may create additional inequalities in access to public education. More precisely, if one does not understand the game and does not invest enough to acquire information on others' preferences, she may have a disadvantage when playing the school choice game. As a policy intervention, education authority can choose to make this information easier to obtain by publishing students' strategies and allowing students to revise their applications upon observing others' strategies as in Amsterdam (De Haan et al. 2015) and Wake County, NC (Dur et al. 2015).

Note that a symmetric Bayesian Nash equilibrium, possibly in mixed strategies, always exists under any of the four information structures by the standard fixed point arguments. We summarize the results on *ex ante* welfare under DA and IA in the following two propositions.

**Proposition 3.** *Under DA, the ex ante welfare of every student under any of the four information structures (UI, OI, CI, and PI) equals  $\sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s})$  in any symmetric equilibrium.*

This implies that there is no gain in *ex ante* student welfare when students receive more information under DA.

Finally, we state our last proposition.

**Proposition 4.** *Under IA, we obtain the following ex ante student welfare comparisons in terms of Pareto dominance in a symmetric equilibrium:*

- (i) *under UI and OI, the ex ante welfare of every student is  $\sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s})$ ;*
- (ii) *CI  $\geq$  OI = UI;*
- (iii) *PI  $\geq$  OI = UI;*
- (iv) *PI can either Pareto dominate or be Pareto dominated by CI.*

The above proposition suggests that it is always beneficial to provide more information on one's own cardinal preferences, but the effect of providing information on others' preferences is ambiguous. To prove part (iv), we use two examples in Appendix A (Sections A.5.4 and A.5.5). The intuition can be shown in the following example: Under PI, it is possible that multiple high-type students at a school play mixed strategies in equilibrium instead of always top-ranking that school, as they compete for the same school seats knowing the presence of other high-type students. Consequently, always top-ranking that school becomes sub-optimal; that school may end up being assigned to a low-type student, leading to a welfare loss. By contrast, under CI in a symmetric Bayesian Nash equilibrium, high-type students do not know the number of other high-type students in the game.

### 3.6 Possible Extensions

Our model considers the sequential acquisition of information, but, in reality, students may acquire information on one's own and others' preferences simultaneously. Given the lack of strategy-proofness and the role of cardinal utility under IA, we expect our results to hold.

For our analysis of information provision, we assume that information acquisition cost is infinite, which is not the case in reality. Here, our experimental results show this limitation is less of a concern, as they call for more information provision by education authority (Section 5). However,

it can be expensive for an educational authority to provide information. A cost-benefit calculation of providing information can be found in Hoxby and Turner (2013). This calculation shows that a cost of \$6 per student can benefit low-income students significantly.

Our model also assumes students have the same ordinal preferences. This is not uncommon when studying the welfare performance of the two mechanisms (Abdulkadiroğlu et al. 2011, Troyan 2012), with the justification that the common-ordinal-preference assumption is plausible in real life. Nonetheless, we realize that an extension to a more general preference domain would be fruitful and leave this to future study.

Finally, our model assumes every student is rational; however, this assumption is not born out in lab or field studies (Chen and Sönmez 2006, He 2014). Further studies might explore a theoretical model with students of heterogeneous sophistication levels, as in Pathak and Sönmez (2008).

Given the above considerations, a laboratory experiment can help us better understand how our theoretical predictions correspond to actual participant decisions in a school choice context.

## 4 Experimental Design

In designing our experiment, we relax our common-ordinal-preference assumption, and allow students to have different ordinal preferences. To simplify the game, we design the payoff distribution so that the two-step acquisition of information on one's own preferences is reduced to only one step. That is, upon learning one's own ordinal preferences, a student learns her cardinal preferences as well, because there is only one possible realization of cardinal preferences consistent with a given ordinal preference.

### 4.1 The Environment

Following our theoretical analyses, we consider a simple environment with three students,  $i \in \{1, 2, 3\}$ , and three schools,  $s \in \{A, B, C\}$ . Each school has one available slot and ranks students using a lottery. Student cardinal preferences are i.i.d. random draws from Table 1. The uncertainty comes from the value of school  $B$ , which can be either better or worse than that of school  $A$ , relaxing the common-ordinal-preference assumption. *Ex ante*, the expected payoff of being assigned to  $B$  is 0.3, which is less than  $1/3$  of the payoff from school  $A$ . In terms of welfare, the inefficiency

has only one source, i.e., it is inefficient to assign a type- $(1, 0.1, 0)$  student to school  $B$  if there is at least one other student of type- $(1, 1.1, 0)$ .

Table 1: Payoff Table for the Experiment

Students	$s = A$	$s = B$	$s = C$
$i \in \{1,2,3\}$	1	0.1 with probability 4/5; 1.1 with probability 1/5	0

Notes: The above payoffs are in dollars. In the experiment, points are used to measure payoffs, with an exchange rate of 100 points = 1 USD.

Assuming that every student is a risk-neutral expected-utility maximizer, we solve all (symmetric) equilibria of the school choice game under either IA or DA for any given information structure. We present detailed derivations and as well as our results in Appendix E. We also derive the results under the assumption that students are risk averse (Appendix F). While risk-averse students are often willing to pay less for information on either one’s own or others’ preferences, the same directional comparison between the IA and DA mechanisms maintains. To measure the incentive to acquire information on 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 from playing the game based on knowing or not knowing one’s own preferences, taking into account that the other two students may or may not know their own preferences. Therefore, we reach the theoretical predictions on student willingness to pay (WTP, henceforth) for OwnValue. Similarly, to measure student WTP for information about others’ preferences (denoted as “OtherValue”), we treat preference realizations as private information. For any given student, we derive the payoff difference from playing the game with and without the knowledge of others’ preferences.

## 4.2 Treatments

In our experiment, we implement a  $2(\text{mechanisms}) \times 2(\text{information to be acquired}) \times 2(\text{information cost})$  factorial design to evaluate the performance of the two mechanisms  $\{IA, DA\}$  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): While DA is dominant strategy incentive compatible, IA is manipulable. However, the welfare comparisons of these two mechanisms are ambiguous,

depending on both the information condition and parameters of the environment.

- (ii) Acquiring OwnValue vs. OtherValue (between-subject): Our theoretical analyses suggest that the incentive to acquire information depends on the type of information to be acquired.
- (iii) Free vs. costly information acquisition (within-subject): While the free information condition allows us to evaluate information provision policies, the costly information acquisition condition better reflects reality. As this factor is implemented within-subject, we also take into account the order effect: For half the sessions, subjects first experience free-info rounds and then costly-info rounds (denoted as “Free-Costly”); for the other half of the sessions, subjects experience costly-info rounds first and then free-info rounds (denoted as “Costly-Free”).

In the free information treatment, participants are provided the information of their own value (or others’ values) for free. In comparison, in the costly information treatment, we use the Becker-DeGroot-Marshak (BDM) mechanism (Becker et al. 1964) to elicit participant’s WTP for one’s own or others’ values for school B. Specifically, each subject is asked to enter her WTP for her own (or others’) values in the interval from  $[0, 15]$ . The server then collects the WTP from each participant and generates a random number between  $[0, 15]$  for each participant independently. If a subject’s WTP is greater than the random number, she finds out the relevant information and pays an amount equal to the random number; otherwise, she does not find out the information and pays zero. To facilitate participant understanding of the BDM mechanism, we provide numerical examples and test understanding by administering a quiz. Our instructions for the BDM mechanism are adapted from those in Benhabib, Bisin and Schotter (2010).

To elicit each participant’s belief about the average WTP of the other two participants in her group, we use the binarized scoring rule (BSR) introduced in 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 2013). As such, it is more robust than the quadratic scoring rule. Specifically, in the BSR, each subject submits a guess for the average WTP of the other two participants. The server then computes the squared error between the guess and the actual average, i.e.,  $SE = (\text{guess} - \text{actual average})^2$ . The server then 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. 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.

### 4.3 Experimental Procedures

In each experimental session, each participant is randomly assigned an ID number and is seated in front of a computer terminal. The experimenter then reads the instructions to the group for the first ten rounds. After this, subjects have the opportunity to ask questions, which are answered in public. Subjects are then given 10 minutes to read the instructions at their own pace and to finish the review questions. After everyone finishes the questions, the experimenter distributes and goes over the answers in public. Afterwards, participants go through twenty rounds of a school choice experiment. After the first ten rounds, the experimenter reads the instructions for the second ten rounds and answers questions. Participants again complete a set of review questions, and then go through the second ten rounds of the experiment.

In the acquiring OwnValue treatments, each round consists of the following stages:

- (i) Each participant is provided with the value distribution (Table 1) to induce common prior.
- (ii) Each participant is asked to rank the schools.

The server then collects rankings, draws the school B value for each subject, generates the tie-breaker, and allocates schools to participants. The allocation outcomes are shared with participants at the end of each round.

- (iii) Each participant acquires her value for school B, either for free or by paying a cost:
  - (a) For the *free* information treatment, each subject receives her own value for school B for free.
  - (b) For the *costly* information treatment, we use the BDM mechanism to elicit each participant's willingness to pay. 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.

The server collects the respective WTP and generates a random number between  $[0, 15]$  for each participant.

(iv) After step (iii), 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 one's own value.
- (b) *Costly* information treatment: her WTP, her random number, and whether she observes her value,
  - i. if she observes her value, she also receives her value, the number of other subject(s) in her group who also observe their value(s);
  - ii. if she does not observe her value, she receives only the number of other subject(s) in her group who observe their value(s).

(v) Each participant is then asked to rank the schools again.

The server again collects the rankings, draws a new set of values for every subject, generates a new tie-breaker for each participant, and allocates the schools.

(vi) At the end of each round, each participant receives the following feedback on her computer monitor:

- (a) For the game without OwnValue acquisition: her ranking, her value, the tie-breaker, her allocation and her payoff; and
- (b) For the game with free or costly OwnValue acquisition: 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. In these treatments, the information provided or acquired is the value for school B for the other two participants in her group.

A given session consists of 20 rounds with either costly or free information for the first ten rounds, and the other condition for the next ten rounds. The order is counterbalanced for each treatment. At the end of 20 rounds, we implement the Holt and Laury lottery choice procedure to elicit subject risk attitude. After telling each subject her payoff from the risk elicitation task, we offer an opportunity for subjects to acquire information on 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 preference for more information in the absence of any instrumental value associated with that information.(Grant, Kajii and Polak 1998, Golman and Loewenstein 2015)

At the end of the experiment, each participant fills out a demographic and strategy survey on the computer and is then paid in private. The experiment is programmed in z-Tree (Fischbacher 2007).

Table 2: Features of Experimental Sessions

Information to Be Acquired	Immediate Acceptance Mechanism		Deferred Acceptance	
OwnValue: Own Preferences	Free-Costly	3×12	Free-Costly	3×12
	Costly-Free	3×12	Costly-Free	3×12
OtherValue: Others' Preferences	Free-Costly	3×12	Free-Costly	3×12
	Costly-Free	3×12	Costly-Free	3×12

Notes: Each session 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-Costly”; and the others with costly information first are denoted as “Costly-Free”.

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. 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 subjects. In addition, we conduct three sessions of DA-OtherValue (Free-Costly) treatment using a z-Tree program with a coding error in the second ten rounds of the experiment, i.e., a participant’s own value is not provided in the second ten rounds. In this case, we use the data from the first ten rounds for these sessions in our data analysis, since the instructions and program for the first half are both correct. Therefore, 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 D; the data are available from the authors upon request.

## 5 Experimental Results

In our discussion of our results, we focus on participants’ willingness-to-pay for information (WTP) and their welfare in the game under various information structures. We present our summary statistics for the key variables in our analysis in Table C3 of Appendix C. We also provide the results for our analyses of individual strategies (i.e., their rank-ordered lists) in Appendix B.

We introduce several shorthand notations in presenting the results. First, let  $x > y, x, y \in \{IA, DA\} \cup \{UI, CI, PI\} \cup \{\{IA, DA\} \times \{UI, CI, PI\}\}$ , denote that a measure under mech-

anism (or information structure)  $x$  is greater than the corresponding measure under mechanism (or information structure)  $y$  at the 5% significance level or less. Second, let  $x \geq y$  denote that a measure under  $x$  is greater than the corresponding measure under  $y$ , but that this difference is not statistically significant at the 5% level.

## 5.1 Willingness to Pay for Information

For our experimental environment, we derive the WTP for risk-neutral and risk averse students in Appendices E and F, respectively, to illustrate the difference between DA and IA. The respective theoretical predictions for risk neutral and risk averse agents for each treatment are tabulated in the last two columns of Table 3. In general, risk aversion predicts a lower WTP in our environment.

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

Treatment	All 6 Sessions	Free-Costly Sessions	Costly-Free Sessions	Theoretical Prediction <sup>a</sup>	
				Risk-Neutral	Risk-Averse
IA OwnValue	6.56 (4.78)	5.56 (4.59)	7.57 (4.75)	[5.2, 8]	[4.9, 7.7]
IA OtherValue	4.51 (4.55)	4.00 (4.55)	5.02 (4.49)	[0, 0.24]	[0, 0.46]
DA OwnValue	4.44 (4.38)	3.16 (4.05)	5.72 (4.33)	0.67	[0.3, 0.4]
DA OtherValue	2.21 (3.16)	1.90 (3.25)	2.52 (3.04)	0	0

Notes: The WTPs are measured in experiment points. There are 6 sessions under each treatment, and each session has 10 rounds with free information and another 10 rounds with costly information. For any given treatment, three sessions have free information rounds first (denoted as Free-Costly); and the other three have costly information first (denoted as Costly-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 of the 72 subjects, half of which are from the Costly-Free treatments, while the other half Free-Costly.

a. The predictions are for risk-neutral and risk-averse subjects respectively, and are derived in detail in Appendices E and F. Under the two treatments of IA, the predictions are intervals, because the WTPs depend on how many other subjects successfully acquire such information. As this is uncertain *ex ante*, the prediction is an interval that takes into account all possibilities.

We can now state our first formal hypothesis.

**Hypothesis 1** (WTP for OwnValue). *A subject's WTP to acquire information on her own preferences under the IA mechanism is greater than that under the DA mechanism; both are positive, i.e.,  $IA > DA > 0$ .*

**Result 1** (WTP for OwnValue). *A subject's WTP to acquire information on her own value under IA is significantly greater than that under DA; both WTPs are positive.*

**Support:** Table 3 presents the session average WTP for each treatment. Allowing correlations within a session and using a one-sided Wilcoxon rank-sum test, we reject the null of no difference in favor of Hypothesis 1 that  $IA > DA$  ( $p = 0.03$ ). Furthermore, the average WTP for one's own value under the IA mechanism is 6.56 (standard deviation or s.d. 4.78), while that under the DA mechanism is 4.44 (s.d. 4.38). Both are significantly different from zero at the 1% level. ■

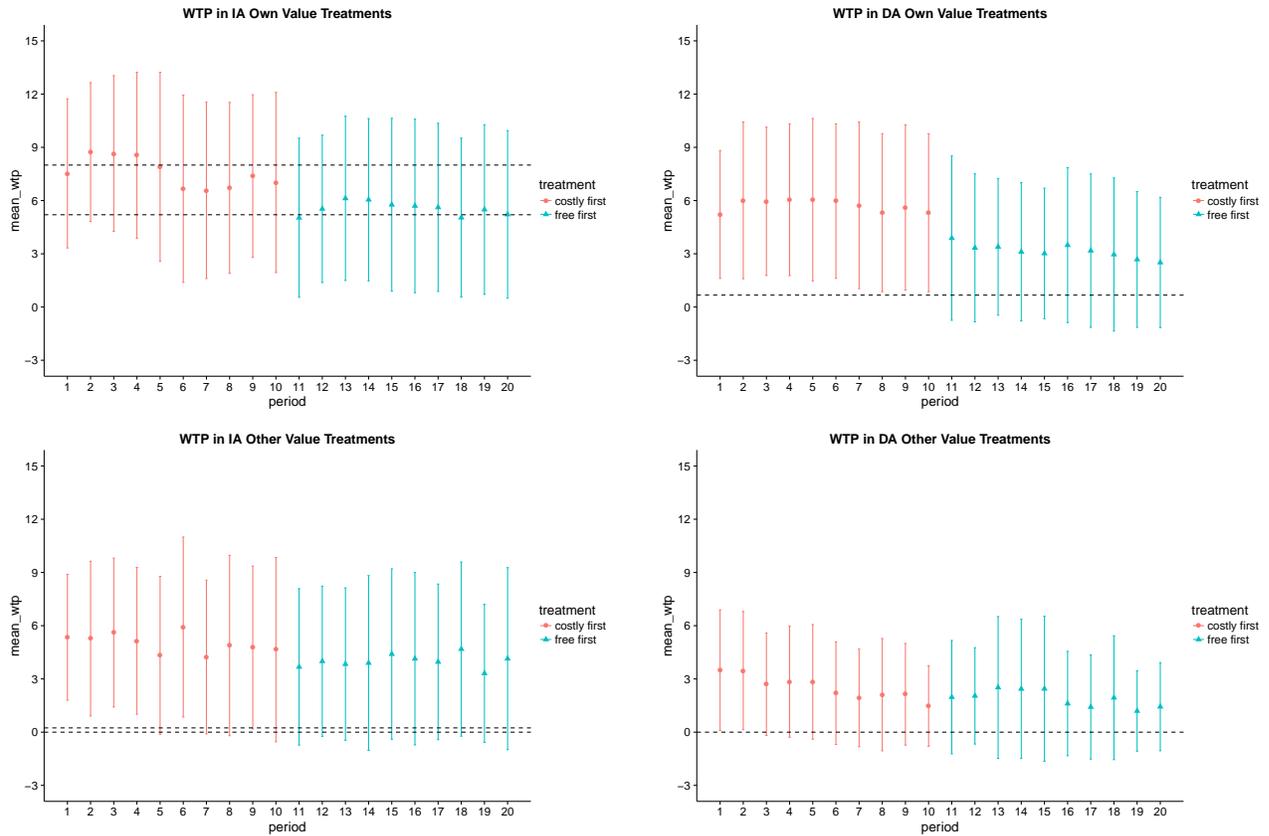


Figure 3: Average WTP for Own Value (upper panel) and Others' Values (lower panel) by Rounds  
 Notes: Horizontal dashed lines denote the theoretical predictions for the WTP of risk-neutral students. Error bars represent one standard deviation. The first ten rounds (costly first, i.e., costly information acquisition rounds played before the free information ones) and last ten rounds (free first, i.e., rounds with free information played before those with costly information acquisition) are from different sessions.

Figure 3 depicts the time series of the average WTP for OwnValue (upper panel) and OtherValue (lower panel), with the theoretical predictions for risk neutral students presented by the horizontal line(s). While the average WTP in IA OwnValue treatment is mostly within the range predicted by theory, [5.2, 8], it is substantially above the risk neutral prediction in any other treatment. This motivates our decomposition of the excess WTP in subsequent subsections.

We next examine a subject's WTP for information on others' preferences in the following hypothesis.

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

**Result 2** (WTP for Others' Values). *A subject's WTP for others' values under the IA mechanism is significantly greater than that under the DA mechanism, but both are significantly different from zero:  $IA > DA > 0$ .*

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

Our results further show that, under either IA or DA, a subject's WTP for her own value is significantly greater than that for others' values ( $p = 0.01$ , one-sided Wilcoxon rank-sum test), consistent with our theoretical predictions. Interestingly, while the WTP for others' values between the two mechanisms is in the direction predicted by theory, we again find that the WTP for others' values lie above the range predicted by theory.

In sum, we find that while the WTP directional comparisons across mechanisms and across one's own versus others' values are consistent with theory, participants indicate a greater WTP for information across treatments. This over-investment in costly information acquisition relative to equilibrium predictions has been observed in other endogenous information acquisition experiments in the context of jury or committee voting (Bhattacharya et al. 2015).<sup>4</sup> In the following, we first investigate the determinants of WTP for information at the subject level (subsection 5.1.1) and by using panel regressions (subsection 5.1.2). Based on these investigations, we then decompose the observed excess WTP into behavioral and cognitive explanatory factors (subsection 5.2).

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<sup>4</sup>The authors explain their observed over-investment as a result of a combination of poor strategic thinking and the quantal response equilibrium model.

### 5.1.1 Determinants of WTP for Information: Subject-Average

We use the following Tobit model to analyze the determinants of the subject average WTP:

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

where  $\varepsilon_i$  is normally distributed, the latent variable  $\overline{WTP}_i^*$  is not observed, and the subject-average WTP,  $\overline{WTP}_i$ , is observed. The latter is obtained by averaging all of subject  $i$ 's WTPs. We use the Tobit model to take into account that  $\overline{WTP}_i$  is censored between  $[0, 15]$  among 18% of our main sample observations (43 out of 241 consistent subjects, defined below).<sup>5</sup> For independent variables (controls), we include the four treatment dummies (therefore no constant) and demographic variables. Moreover, we consider the effects of the following factors:

- (i) **Misunderstanding DA:** This variable measures the proportion of times a subject plays a dominated strategy in the free information rounds. It is negatively correlated with a subject's understanding of the school choice game under the DA mechanism. Note that there is no similar measure for the IA mechanism, which lacks a dominant strategy.
- (ii) **Costly-Free:** This dummy variable indicates that a session follows a costly to free information acquisition order. Playing the game with costly information acquisition in the first ten rounds imposes a higher cognitive load as participants must learn both the school choice game and the information acquisition game. This greater cognitive load, reflected in Table 3, may lead to a sub-optimal WTP.
- (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 reflect's a subject's "curiosity," or general taste for information.
- (iv) **Risk aversion:** Risk aversion is measured by the switching point in the Holt-Laury lottery choice menu. Following the literature, we define a *consistent* subject as one who exhibits one switching point and chooses the right column in the last lottery choice. In our sample, we find that 241 of 288 subjects are consistent; among these 78% are risk-averse, 16% risk-neutral,

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<sup>5</sup>In a robustness check, we find quantitatively and qualitatively similar results when we use linear models (Table C4 in Appendix C).

and 7% risk-loving. Theoretically, a greater degree of risk aversion suggests a lower WTP for information (Table 3 and Appendix F).

Of these four factors, the first two measure subject understanding of the game, while the last two measure subject preferences. Table 4 presents four Tobit specifications investigating the determinants of subject-average WTP. Column 1 includes the full sample, whereas columns 2-4 include only consistent subjects. Column 4 adds more controls but excludes observations with missing demographic information.

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, we find that misunderstanding DA and curiosity are each positively correlated with WTP. Furthermore, we find that the timing of the information acquisition game matters. When subjects have to learn both the school choice mechanism and the information acquisition game in the first ten rounds, i.e.,  $Costly-Free = 1$ , they exhibit a higher WTP. This is consistent with previous experimental findings that a higher cognitive load can cause sub-optimal play (Bednar, Chen, Liu and Page 2012). Lastly, consistent with our theoretical prediction, more risk averse subjects show a lower WTP (column 3); however, risk aversion becomes insignificant once we include demographic controls (column 4).

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

We next explore within-subject time-series variations by using panel data methods on the subject-round observations. Similar to our analysis of the subject-average WTP (Table 4), we take into account that WTP is bounded within  $[0, 15]$ , and specify the following Tobit model:

$$WTP_{i,t}^* = \alpha_i + \beta_1 high\_B \times IA\_OtherValue_{i,t} + \beta_2 high\_B \times DA\_OtherValue_{i,t} + \beta_3 WTP\_Guess_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, \quad (1)$$

$$WTP_{i,t} = \max\{0, \min\{WTP_{i,t}^*, 15\}\},$$

where  $i$  indexes subjects and  $t$  indexes rounds (within each session). Given the non-linear nature of the Tobit model, we cannot consistently estimate  $\alpha_i$  as subject fixed effects with a short panel (ten rounds). Consequently, we use a random effects Tobit model. For the above specification, we

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

	(1) Full Sample	(2) Sub-sample 1	(3) Sub-sample 1	(4) Sub-sample 2
IA_OwnValue	6.45*** (0.56)	6.26*** (0.57)	5.22*** (1.10)	5.77*** (1.74)
IA_OtherValue	4.32*** (0.62)	4.05*** (0.72)	3.46*** (1.21)	3.91** (1.91)
DA_OwnValue	4.13*** (0.71)	3.78*** (0.82)	2.94*** (1.07)	3.60** (1.71)
DA_OtherValue	1.47*** (0.45)	1.01** (0.47)	0.91 (1.13)	1.98 (1.79)
Misunderstanding DA <sup>a</sup>			6.85*** (2.02)	6.29*** (2.21)
Curiosity			0.34*** (0.05)	0.33*** (0.04)
Costly-Free			1.88*** (0.45)	1.87*** (0.36)
Risk Aversion			-0.28** (0.13)	-0.20 (0.13)
Female				-0.87* (0.48)
Graduate Student				-0.72 (0.51)
Black				-1.09* (0.59)
Asian				-1.75** (0.69)
Hispanic				-0.83 (0.57)
<i>N</i>	288	241	241	233

Notes: The outcome variable is the subject-level average WTP for information. There are 42 (out of 241, 17%) subjects with an average WTP = 0 and one subject with WTP = 15. Columns (2)-(4) include only consistent subjects. Column (4) further excludes observations with missing age/gender/ethnicity information but includes the following controls: age, ACT score, SAT score, dummy for ACT score missing, dummy for SAT score Missing, and dummy for degree missing. Standard errors clustered at the session level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

a. "Misunderstanding DA" is defined as the percentage of times when a subject plays dominated strategies in the OwnValue or OtherValue treatment of DA in rounds without information acquisition. We find a mean = 0.09 (s.d. = 0.14) among all subjects ( $n = 144$ ) who play the information acquisition game under DA. Their rounds without information acquisition, i.e., with no or free information provision, are considered in the construction of this variable. This variable equals zero for the IA treatments.

run each set of analyses with all four treatments both individually and pooled.<sup>6</sup>

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 (= 110) under the treatment IA OtherValue, and zero

<sup>6</sup>For robustness checks, we present the respective fixed effects (Table C5) and random effects panel regressions (Table C6) in Appendix C.

otherwise. We also include  $high\_B \times DA\_OtherValue_{i,t}$ , which we define similarly.<sup>7</sup> Our theory 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 (see Appendix E.6). These results are confirmed.

In addition, one key explanatory variable is  $WTP\_Guess_{i,t}$ , which is subject  $i$ 's estimate of her opponents' average WTP in round  $t$ . Our theory predicts that  $i$ 's own WTP should be negatively correlated with  $WTP\_Guess_{i,t}$ , albeit weakly (see Appendices E.5 and E.6).<sup>8</sup>

Finally, other controls include accumulated wealth at the beginning of the round, round (i.e., a linear time trend), round in Free-Costly sessions, and the lagged average WTP of other players. Depending on the specification, we also include the lagged guess of others' WTP ( $WTP\_Guess_{i,t-1}$ ).

We present the results of our panel data analyses in Table 5, where the three columns differ in the inclusion or exclusion of  $WTP\_Guess_{i,t}$  and its lag. From Table 5, we see that the coefficient on  $WTP\_Guess_{i,t}$  is positive and significant, contrary to our theoretical predictions. Our results also show that subjects lower their excess WTP over time. Finally, we find that the coefficients on our four factors (Misunderstanding DA, Curiosity, Costly-Free, and Risk Aversion) are similar to those in Table 4, although that on Risk Aversion is always insignificant.

## 5.2 Decomposition of a subject's WTP

In this section, we explore our observation that subjects over-invest in information acquisition by decomposing our observed WTP treatment-by-treatment according to the following factors:

- (i) Cognitive load: How playing Costly-info rounds before Free-info rounds impacts results.
- (ii) Learning: How WTP changes over rounds.
- (iii) Misunderstanding DA: How WTP is correlated with playing dominated strategies under DA.
- (iv) Conformity: How one's own WTP is affected by the expectation of others' WTP.
- (v) Curiosity: How WTP for school B value is correlated with WTP for non-instrumental information.

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<sup>7</sup>For the other treatments, IA or DA OwnValue, it is impossible to define such a variable, because subjects do not know their own value of school B when deciding whether or not to acquire information.

<sup>8</sup>One might be concerned with the endogeneity of  $WTP\_Guess_{i,t}$ . That is, there may be some common shocks in round  $t$  which make subject  $i$ 's  $WTP_{i,t}$  and  $WTP\_Guess_{i,t}$  higher. We address this possibility with an IV approach in Tables C5 and C6 in Appendix C, from which we interpret that endogeneity is not an issue for our analyses.

Table 5: Determinants of WTP: Random Effects Panel Tobit Analyses

	(1)	(2)	(3)
high_B $\times$ IA_OtherValue	3.38** (1.41)	3.47** (1.35)	3.38*** (1.11)
high_B $\times$ DA_OtherValue	-0.49 (1.03)	-0.42 (0.83)	-0.50 (1.05)
Accumulated wealth up to $t - 1$	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Successfully acquired info in $t - 1$	0.30 (0.30)	0.13 (0.28)	0.27 (0.27)
Round	-0.20** (0.09)	-0.27** (0.11)	-0.20** (0.08)
Round $\times$ Free-Costly	0.11 (0.10)	0.12 (0.11)	0.11 (0.09)
Average WTP of others in $t - 1$	-0.04 (0.03)	0.12*** (0.03)	-0.04 (0.03)
$WTP\_Guess_{i,t-1}$ : Guess of others' WTP in $t - 1$	-0.04 (0.08)	0.23*** (0.06)	
$WTP\_Guess_{i,t}$ : Guess of others' WTP in $t$	0.91*** (0.11)		0.90*** (0.09)
Misunderstanding DA	7.06*** (2.69)	8.86*** (3.08)	7.04*** (2.70)
Curiosity	0.38*** (0.06)	0.47*** (0.07)	0.38*** (0.06)
Costly-Free	1.78* (1.07)	2.93** (1.27)	1.76* (1.05)
Risk Aversion	-0.29 (0.20)	-0.27 (0.22)	-0.29 (0.19)
IA_OwnValue	2.37** (0.91)	4.06*** (0.93)	2.28** (0.96)
IA_OtherValue	0.48 (1.05)	1.20 (1.20)	0.43 (0.91)
DA_OwnValue	2.11* (1.14)	2.31* (1.28)	2.08** (1.03)
# of observations	2097	2097	2097
# of subjects	233	233	233

Notes: The regression sample is the same as that in Column (5) in Table 6. There are 233 subjects each of whom has 9 observations from 9 rounds. 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, and dummy for degree missing. Standard errors clustered at session level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

(vi) Risk aversion: How WTP is correlated with risk aversion.

To perform our decomposition, we first estimate the Tobit model, as in equation system (1), for each separate treatment (Columns (1) - (4) in Table 6). Doing so allows each factor to have a different effect in a given treatment. Indeed, we find that coefficients of some of our key variables

Table 6: Determinants of WTP: Separate and Pooled Random Effects Panel Tobit Analyses

	IA		DA		Pooled (5)
	OwnValue (1)	OtherValue (2)	OwnValue (3)	OtherValue (4)	
high_B × IA.OtherValue		3.95*** (1.14)			3.38*** (1.19)
high_B × DA.OtherValue				-0.51 (0.97)	-0.50 (1.03)
Accumulated wealth	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Successfully acquired info in $t - 1$	0.18 (0.49)	-0.36 (0.62)	0.45** (0.20)	0.40 (0.39)	0.27 (0.26)
Round	-0.20 (0.13)	-0.16 (0.14)	-0.26 (0.17)	-0.43 (0.28)	-0.20** (0.09)
Round × Free-Costly	0.22*** (0.07)	0.24 (0.20)	0.07 (0.10)	-0.16 (0.20)	0.11 (0.09)
Average WTP of others in $t - 1$	-0.05** (0.02)	0.05 (0.07)	-0.11** (0.05)	-0.01 (0.05)	-0.04 (0.02)
Guess of others' WTP in $t$	0.88*** (0.17)	0.75*** (0.19)	0.95*** (0.11)	1.04*** (0.20)	0.90*** (0.09)
Misunderstanding DA			6.55 (4.54)	8.02 (5.83)	7.04*** (2.45)
Curiosity	0.31*** (0.12)	0.63*** (0.18)	0.26 (0.21)	0.46*** (0.09)	0.38*** (0.07)
Costly-Free	-0.36 (2.73)	2.72 (3.15)	2.98 (3.47)	1.47 (5.41)	1.76 (1.11)
Risk Aversion	-1.49*** (0.41)	-0.31 (0.39)	-0.41 (0.37)	0.37** (0.18)	-0.29 (0.20)
IA_OwnValue					2.28** (0.92)
IA_OtherValue					0.43 (0.99)
DA_OwnValue					2.08** (1.00)
# of observations	549	495	558	495	2097
# of subjects	61	55	62	55	233

Notes: Estimates are from random effects panel Tobit models for each treatment separately and pooled. The regression sample in Column (5) is the same as Column (3) in Table 5. 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, and dummy for degree missing. Standard errors clustered at session level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

change their significance level (e.g., “Round” and “Risk Aversion”) or even switch signs across treatments (e.g., “Round × Free-Costly” and “Costly-Free”). As a comparison, we present our results based on the pooled regression in Column (5)), which is the same regression as in Column (3) of Table 5.

Based on these estimated coefficients, Table 7 presents the decomposition of subject WTP for information.<sup>9</sup> These results indicate that our six factors can explain the majority of the observed WTP; without these factors, WTP for information is close to the theoretical prediction, except in the IA OwnValue treatment, where subjects have insufficient WTP after controlling the factors. We now discuss the effect of each factor in detail.

- (i) **Cognitive Load:** Our regression results indicate that the Costly-Free order is associated with an average 1.76 points of extra WTP in every round among all treatments (Table 6, Column (5)), but that this effect is not present in the IA OwnValue treatment (Table 6, Column (1)). Moreover, the order also affects learning over rounds based on the coefficients on “Round” and “Round  $\times$  Free-Costly”: in Costly-Free sessions, learning over rounds decreases the WTP faster. By the 10th round, we find that WTP in Costly-Free sessions is reduced by 1.80 points relative to the first round, while this reduction is only 0.81 in the Free-Costly sessions. To quantify the effect of cognitive load, we consider the counterfactual of replacing Costly-Free by Free-Costly. That is, we set all “Costly-Free” to zero and all “Round  $\times$  Free-Costly” equal to “Round.” We then measure the effect of cognitive load as the difference between the model prediction based on current variable values and the prediction under the counterfactual. Both predictions are censored to guarantee that the predicted WTP falls between 0 and 15. Table 7 reports the average effect along with its standard deviation. Specifically, we find that the presence of cognitive load increases WTP by 0.36 to 0.99 points, except in the IA OwnValue treatment, where the sign is opposite.
- (ii) **Learning over rounds:** To assess learning over rounds, we consider the counterfactual of replacing a subject’s behavior in rounds 2-9 with that of round 10. Note that round 1 is not omitted from our regression as we do not have the lagged values for any variable in that round. Using the same censoring as above, we find that the estimated effect of learning, or the difference between the prediction with the observed variable values and the prediction under the counterfactual, accounts for between 0.10 to 0.70 points of WTP.
- (iii) **Conformity:** Our conformity measure reflects the extent to which subjects positively respond

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<sup>9</sup>As a robustness check, decomposition based on pooled regressions (Column (5) in Table 6) are presented in Table C7 in Appendix C, which shows similar results.

Table 7: Decomposition of Subject WTP for Information

	(1) IA OwnValue	(2) IA OtherValue	(3) DA OwnValue	(4) DA OtherValue
WTP: data	6.49 (4.86)	4.29 (4.67)	4.30 (4.30)	1.78 (2.81)
Model prediction <sup>a</sup>	6.40 (3.16)	4.18 (2.98)	4.26 (2.97)	1.69 (1.95)
(i) Cognitive load <sup>b</sup>	-0.70 (0.74)	0.36 (0.49)	0.99 (1.02)	0.45 (0.66)
(ii) Learning over rounds <sup>b</sup>	0.30 (0.46)	0.10 (0.34)	0.63 (0.52)	0.71 (0.81)
(iii) Conformity <sup>b</sup>	4.10 (1.99)	2.10 (1.62)	2.78 (2.13)	1.30 (1.62)
(iv) Misunderstanding DA <sup>b</sup>			0.41 (0.70)	0.25 (0.62)
(v) Curiosity <sup>b</sup>	1.36 (1.35)	1.69 (2.04)	0.75 (1.01)	0.57 (1.17)
(vi) Risk aversion <sup>b</sup>	-1.43 (1.28)	-0.24 (0.28)	-0.51 (0.48)	0.31 (0.37)
Total <sup>c</sup>	3.60 (2.49)	3.17 (2.79)	3.73 (2.92)	1.68 (1.95)
Explained by other factors <sup>d</sup>	2.88 (3.93)	1.13 (3.82)	0.58 (2.98)	0.11 (2.05)
<b>Theoretical prediction<sup>e</sup></b>	[5.2,8]	[0, 0.24]	0.67	0
# of Observations	549	495	558	495
# of Subjects	61	55	62	55

Notes: Decompositions are based on the random effects Tobit model for each treatment (Columns (1) - (4) in Table 6). 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 "Cognitive load," "Conformity," "Misunderstanding DA," 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" 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. "Explained by other factors" is the difference between the observed WTP and the total WTP explained by the six factors.

e. These are the theoretical predictions for risk neutral subjects.

to their beliefs about others' behavior,  $WTP\_guess$ . Our results for conformity show that expecting others to pay one extra point results in an average additional 0.90 points for WTP (Column (5) in Table 6).

Although the theory predicts a negative correlation between one's own WTP and  $WTP\_guess$ , we consider the counterfactual where the correlation is zero. That is, in the counterfactual, there is no effect of  $WTP\_guess$  on WTP. Our results show that this can explain 1.30 to 4.10

points of the observed WTP, or 49% to 73%, indicating that this is the single most important factor in explaining our observed WTP.

- (iv) **Misunderstanding DA:** Our misunderstanding DA measure is the fraction of times that a subject plays dominated strategies in the DA treatment rounds without information acquisition. Results in Table 6 show that misunderstanding DA increases a subject's WTP.

Similarly, to quantify its effect in the two DA treatments, we predict the WTP under the counterfactual without any misunderstanding of the mechanism (i.e., setting the variable to zero). We then calculate the difference between the model prediction with the observed variable values and the prediction under the counterfactual. The results in columns (3) and (4) in Table 7 show that the effect is 0.41 under DA OwnValue and 0.25 under DA OtherValue.

- (v) **Curiosity:** From the regression in Column (5) of Table 6, we see that a 1 point increase in WTP to pay for non-instrumental information is associated with 0.38 additional points of WTP in each round.

We also 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. After similar calculations, we find that curiosity explains 0.57 to 1.69 points of the observed WTP.

- (vi) **Risk Aversion:** Risk aversion is measured by a subject's switching point in the Holt-Laury lottery choice game. Our results show that being more risk averse is correlated with a lower WTP, which is consistent with our theoretical predictions, although this result is insignificant (Table 6, Column (5)). We further find that this correlation is heterogeneous across treatments, and becomes positive in the DA OtherValue treatment.

We also consider the counterfactual where every subject 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 0.51 to 1.43 points, except when it increases WTP in the DA OtherValue treatment.

Overall, we find that the above six factors combined account for the total explained WTP ranging from 1.68 to 3.73 points, or 55% to 94% of the observed WTP. The remaining WTP is similar to the level predicted by our theory for the two DA treatments. However, it is below the

theoretical prediction level for the IA OwnValue treatment (2.88 versus [5.2, 8]), and substantially above the theoretical prediction for the IA OtherValue (1.13 versus [0, 0.24]). These results may reflect the difficulty of playing the game under IA.

### 5.3 Welfare Analysis

We now turn to our welfare analysis by investigating the effects of information provision and the effects of information acquisition on welfare. Welfare is measured on two dimensions: the payoffs that subjects receive in the experiment and the efficiency of the allocation outcome. An allocation is deemed efficient if a high-B subject, whose school-B valuation is 110, is matched with school B whenever such a subject exists.

#### 5.3.1 Effects of Information Provision on Welfare

Similar to the theoretical analyses (Appendix E), we first consider three information structures without information acquisition: (i) UI (UnInformed), (ii) CI (Cardinally Informed), and (iii) PI (Perfectly Informed).<sup>10</sup> The *ex ante* welfare for risk-neutral subjects and the allocation efficiency are summarized in Table 8 (columns (2) and (4)). Based on this analyses, we derive the following three hypotheses:

**Hypothesis 3** (Efficiency: IA). *With free information provision, the ex ante subject welfare and the fraction of efficient allocations under IA follow the order of  $UI < CI = PI$ . Moreover, the allocation is always efficient under either CI or PI.*

**Hypothesis 4** (Efficiency: DA). *With free information provision, the ex ante subject welfare and the fraction of efficient allocations under DA follow the order of  $UI < CI = PI$ . However, the allocation is not always efficient under either CI or PI.*

**Hypothesis 5** (Efficiency: Comparing IA with DA). *With free information provision, the ex ante subject welfare and the fraction of efficient allocations follow the order,  $IA = DA$  under UI, and  $IA > DA$  under either CI or PI.*

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<sup>10</sup>By design, CI is equivalent to OI (everyone is informed of her ordinal preferences but not others' preferences).

**Result 3.** (i) *There is no difference in subject payoffs or allocation efficiency between DA and IA under UI; (ii) Information provision transforming UI into CI improves both subject payoffs and allocation efficiency under both DA and IA, with a greater effect for IA; (iii) Information provision transforming CI to PI does not improve the performance of either DA or IA; and (iv) The outcomes of IA under either CI or PI are closer to the efficient outcome relative to those of DA under either CI or PI.*

**Support:** Parts (i)-(iii) are directly from the test results in Table 8. Columns (1) and (3) in Table 8 report the observed payoff and proportion of efficient allocations under each information condition, 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. For Part (iv), outcomes of IA under CI or PI achieve 93-96% of maximum payoffs and result in efficient allocations among 89-94% of all games; as a comparison, outcomes of DA under CI or PI on average achieve only 87-89% of maximum payoffs and result in efficient allocations among 81-84% of all games. ■

Given the design of the experiment, we perform both within- and between-treatment tests. For instance, to test the effect of information provision under IA (UI to CI), we use the Wilcoxon matched-pairs signed-ranks test, since the same group of subjects plays the game under both UI and CI. To test if IA and DA reach the same level of efficiency under CI, we use a Wilcoxon rank-sum (or MannWhitney) test for two independent samples, as no individual experiences both treatments.

### 5.3.2 Effects of Information Acquisition

We now turn to the effects of costly information acquisition on welfare. As the information acquisition technology results in a endogenous probability of receiving the “hard news,” there are likely both informed and uninformed subjects. We thus expect the outcomes to fall between no information and free information provision, leading to our final set of hypotheses.

**Hypothesis 6** (Efficiency: IA). *With costly information acquisition and not taking into account its costs, the ex ante subject welfare and the fraction of efficient allocations under IA follow the order of  $UI < (\text{Acquiring OwnValue})$  and  $CI = (\text{Acquiring OtherValue})$ . Moreover, the allocation*

Table 8: Effects of Information Provision on Payoffs and Allocation Efficiency

	Payoff		Fraction(Efficient Allocation)	
	Observed in Experiment (1)	Theoretical Prediction (2)	Observed in Experiment (3)	Theoretical Prediction (4)
<i>A: IA OwnValue (# obs.:720)</i>				
UI	42.51 (51.12)	43.33	0.69 (0.49)	0.68
CI	50.67 (52.52)	52.93	0.94 (0.29)	1.00
Test: $H_0: UI = CI; H_1: UI < CI$				
p-value	0.01		0.01	
<i>B: IA OtherValue (# obs.: 720)</i>				
CI	49.13 (51.90)	52.93	0.89 (0.35)	1.00
PI	49.12 (52.20)	52.93	0.91 (0.34)	1.00
Test: $H_0: CI = PI; H_1: CI \neq PI$				
p-value	0.92		0.35	
<i>C: DA OwnValue (# obs.: 720)</i>				
UI	42.96 (48.93)	43.33	0.71 (0.48)	0.68
CI	47.22 (54.92)	48.67	0.84 (0.43)	0.87
Test: $H_0: UI=CI; H_1: UI<CI$				
p-value	0.04		0.04	
<i>D: DA OtherValue (# obs.: 1080)</i>				
CI	45.90 (49.96)	48.67	0.81 (0.39)	0.87
PI	46.09 (49.53)	48.67	0.81 (0.40)	0.87
Test: $H_0: CI = PI; H_1: CI \neq PI$				
p-value	0.86		0.86	
<i>E: Comparison between IA &amp; DA</i>				
Test: $H_0: (IA\ UI) = (DA\ UI); H_1:(IA\ UI) \neq (DA\ UI)$				
p-value	1.00		1.00	
Test: $H_0: (IA\ CI) = (DA\ CI); H_1:(IA\ CI) > (DA\ CI)$				
p-value: OwnValue <sup>a</sup>	0.01		0.01	
p-value: OtherValue <sup>a</sup>	0.02		0.02	
$H_0: (IA\ PI) = (DA\ PI); H_1:(IA\ PI) > (DA\ PI)$				
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 also presents 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 OtherValues treatments, respectively.

*is always efficient under either CI or (Acquiring OtherValue).*

**Hypothesis 7** (Efficiency: DA). *With costly information acquisition and not taking into account its costs, the ex ante subject welfare and the fraction of efficient allocations under DA follow the order of  $UI < (\text{Acquiring OwnValue})$  and  $CI = (\text{Acquiring OtherValue})$ . However, the allocation is not always efficient under either CI or (Acquiring OtherValue).*

**Hypothesis 8** (Efficiency: Comparing IA with DA). *With costly information acquisition and not taking into account its costs, in terms of the ex ante subject welfare and the fraction of efficient allocations,  $IA > DA$  under either (Acquiring OwnValue) or (Acquiring OtherValue).*

**Result 4.** *When we do not take information acquisition cost into account, we obtain the results: (i) Acquiring OwnValue improves both subject payoffs and allocation efficiency for both IA and DA, with a greater effect for IA; (ii) Acquiring OtherValue does not affect either subject payoffs or allocation efficiency of IA or DA; (iii) Outcomes of IA under OwnValue or OtherValue are closer to the efficient outcome relative to those of DA under OwnValue or OtherValue.*

**Support:** Table 9 reports the means and standard deviations (in parentheses) of payoffs, the fraction of efficient allocations by information structure, the fraction of having successfully acquired information, the WTP for information, and costs of information acquisition. Similar to before, 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 are randomized in each round. This design feature enables us to perform both within- and between-treatment tests (parts (i) and (ii)). Part (iii) is obtained from simple calculations. With the acquisition of information on OwnValue, IA achieves 89% of maximum payoffs and efficient allocations among 83% of all games; as a comparison, while DA achieves 80% of maximum payoffs and efficient allocations among 73% of all games. Similarly, with the acquisition of information on OtherValues, IA achieves 97% of maximum payoffs and 96% efficient allocations, whereas DA achieves only 87% and 82%. ■

Table 9 also 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 9: Effects of Information Acquisition on Payoffs and Allocation Efficiency

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

Notes: This table presents p-values for the Wilcoxon matched-pairs signed-ranks tests and Wilcoxon rank-sum (or MannWhitney) 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. "Costs paid" measures the actual costs subjects paid in the experiment.

Table 10: Welfare Analyses of Information Acquisition and Provision

<b>Panel A: Effects of Information Acquisition and Provision</b>					
	Information Provision		Information Acquisition (Observed Effects)		
	Welfare effect <sup>a</sup>		Welfare effect <sup>a</sup>		Pr(Info Acquired)
	Theoretical	Observed	w/ low cost <sup>b</sup>	w/ high cost <sup>b</sup>	
IA OwnValue	9.60	8.16	2.30	0.22	0.44
IA OtherValue	0	-0.01	0.09	-1.23	0.28
DA OwnValue	5.34	4.26	-0.28	-1.57	0.30
DA OtherValue	0	0.42	-0.98	-1.45	0.14

<b>Panel B: Welfare Effects (relative to UI) of Counterfactual Policies</b>					
	<i>Laissez-Faire Policy</i>		<i>Counterfactual 1</i>		<i>Counterfactual 2</i>
	Costly Info Acquisition		Free OwnValue, Costly OtherValue		Free OwnValue
	w/ low cost <sup>b</sup>	w/ high cost <sup>b</sup>	w/ low cost <sup>b</sup>	w/ high cost <sup>b</sup>	& 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: Panel A shows the estimates from Table 9; Panel B presents the welfare effects of information acquisition and information provision relative to UI (i.e., nobody knows her own preferences).

a. Given a treatment, welfare effect measures the difference in average payoff (per round, per subject) with costly information acquisition (or free information provision) and that without it, while the costs of information acquisition are taken into account.

b. “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. With either of the technologies, subjects do not pay if they do not successfully obtain information.

(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 effects of information acquisition, it is necessary to consider the costs. Our experiment can be considered a lower cost bound (labeled as “low cost”), because one pays half of her WTP in expectation only if information is acquired. The statistics in Table 9 show that the actual costs paid by subjects in each treatment is 22-34% of the WTP on average.<sup>11</sup> In this case, costly information acquisition is welfare-improving in the IA OwnValue treatment as it increases the average payoff for each subject in each round by 2.3 points. However, in the IA OtherValue treatment, it is essentially welfare-neutral, yielding only 0.09 points in profits. In both DA treatments, costly information acquisition is welfare-decreasing.

To determine “high cost,” we use the same information acquisition technology as in the experiment except that subjects have to pay their WTP instead of the random number when successfully acquiring information. When subjects’ incentive issues are assumed away, this leads to the same

<sup>11</sup>Given the experimental design, when one’s WTP is  $w$ , the expected cost of information acquisition is  $w^2/30$ .

WTP as well as the same probability of acquiring information, which allows us to use our experimental data to calculate welfare. Doing so, we find that the net loss for each subject in each round ranges from 1.23 in the IA OtherValue treatment to 1.57 in the DA OwnValue, while the only net gain is observed in the IA OwnValue treatment (0.22).

### 5.3.3 Total Welfare Effects of Information Provision

Based on the above results, we are now ready to calculate the welfare effects of different policies of information provision. More specifically, we focus on the following three types of policies, measuring welfare relative to the UI baseline where no one knows her own preferences:

- (i) **Laissez-Faire Policy:** The education authority does not provide information but let students conduct information acquisition as they wish with either the lower- or higher-cost technology.
- (ii) **Free OwnValue and OtherValue:** The education authority makes all information available.
- (iii) **Free OwnValue and Costly OtherValue:** The education authority makes all information relevant to OwnValue available but does not provide information on OtherValues. This policy corresponds to policies employed by many school districts where information about school characteristics is readily available, but information on others' strategies is not. Here students must rely on historical strategies to infer others' strategies for the current year.

With the estimated effects of information acquisition and provision, we can calculate the welfare, measured by the student average payoff in each round, for each policy. Our results are summarized in Panel B of Table 10. 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 ( $-0.01$ ).

To analyze 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 either cost assumption ( $4.55 - 2.25$  or  $4.55 - 4.33$ ). Then only those who have successfully acquired OwnValue can engage in acquiring OtherValue, or 44% of our subjects. We further assume that this leads to 44% of the net payoff gain of acquiring OtherValue ( $44\% \times (1.38 - 1.29)$ ) or

$44\% \times (1.38 - 2.61)$ ).<sup>12</sup> Similarly, for the free-OwnValue-costly-OtherValue policy, we take into account the effect of providing OwnValue and that of letting students acquire OtherValue (given that they know OwnValue already).

The results of this analysis show that making both OwnValue and OtherValue freely available leads to an additional 8.15 points for every subject in each round under IA, or 4.68 points under DA. When the cost is low, the laissez-faire policy increases average payoffs under IA but not under DA; when the cost is high, this benefit disappears. In comparison, the free-OwnValue-costly-OtherValue policy is always welfare-improving. When the cost is low, this policy increases the average payoffs by 0.11 points more than that of the free-OwnValue-free-OtherValue policy. However, this small advantage disappears when the cost is high. Unexpectedly, there is always a welfare gain to providing free information on others' preferences under DA. Theoretically, information on others' preferences should not affect student strategies due to the mechanism's strategy-proofness. However, due to the excessive WTP for information, the free provision of information reduces the original wasteful investment in information acquisition. This result has strong implications for school districts using DA by suggesting that the educational authorities should actively provide information on others' preferences instead of ignoring its demand because of the strategy-proofness of DA.

## 6 Conclusion

This paper provides new insights for designing better school choice programs by studying endogenous information acquisition and the effects of information provision. Specifically, we provide both theoretical and experimental evidence that the two popular mechanisms, DA and IA, provide heterogeneous degrees of incentives for students to acquire information on preferences.

Our results show that better information on one's own preferences improves student-school match quality, which is in line with recent calls for better information provision on school quality. However, our experimental results also show that students tend to over-invest in information acquisition. Therefore, it suggests that free or less costly information reduces both students' and

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<sup>12</sup>This is a simplification assumption, as we ignore the fact that the game with this two-stage information acquisition will have both informed and uninformed players. However, given the effects of acquiring OtherValue, we do not expect our conclusion on the policy comparison to change much under more plausible assumptions.

parents' wasteful investments in information acquisition.

Our results further show that acquiring information on others' preferences is related to the gaming aspect of school choice, and that this incentive is determined by a mechanism's strategy-proofness. Theoretically, only a non-strategy-proof mechanism should incentivize students to acquire information on others' preferences. Moreover, if students have learned their own preferences, information on others' preferences affects the redistribution of welfare rather than promoting better matches. To some extent, this incentive to learn others' preferences measures how difficult it is for each student to play the game. Our findings thus reveal a new cost associated with non-strategy-proof mechanisms.

Finally and more importantly, our experiment shows that a strategy-proof mechanism such as DA is not enough to prevent wasteful investments in acquiring others' preferences. In our experiment, students still over-invest in learning others' preferences, even though the strategy-proofness of DA makes such information useless. This over-investment is more severe among those expecting that others are paying generously for information, those who do not understand the school choice game, and those who are more curious. We find that this wasteful investment can be avoided or reduced by making information on others' preferences freely available. These results thus call for information provision that is beyond what has been considered in practice.

## References

- Abdulkadiroğlu, Atila and Tayfun Sönmez**, "School Choice: A Mechanism Design Approach," *Amer. Econ. Rev.*, June 2003, 93 (3), 729–747.
- \_\_\_, **Yeon-Koo Che, and Yosuke Yasuda**, "Resolving Conflicting Preferences in School Choice: The "Boston Mechanism" Reconsidered," *American Economic Review*, 2011, 101 (1), 399–410.
- Artemov, Georgy**, "School Choice Mechanisms, Information Acquisition and School Rankings," 2016. Unpublished Manuscript.
- Bade, Sophie**, "Serial dictatorship: The unique optimal allocation rule when information is endogenous," *Theoretical Economics*, 2015, 10 (2), 385–410.
- Barlevy, Gadi and Pietro Veronesi**, "Information Acquisition in Financial Markets," *The Review of Economic Studies*, 2000, 67 (1), 79–90.

- Becker, Gary M., Morris H. DeGroot, and Jacob Marschak**, “Measuring utility by a single-response sequential method,” *Behavioral Science*, 1964, 9 (3), 226–232.
- Bednar, Jenna, Yan Chen, Tracy Xiao Liu, and Scott Page**, “Behavioral spillovers and cognitive load in multiple games: An experimental study,” *Games and Economic Behavior*, 2012, 74 (1), 12 – 31.
- Benhabib, Jess, Alberto Bisin, and Andrew Schotter**, “Present-bias, quasi-hyperbolic discounting, and fixed costs,” *Games and Economic Behavior*, 2010, 69 (2), 205 – 223.
- Bergemann, Dirk and Juuso Valimaki**, “Information Acquisition and Efficient Mechanism Design,” *Econometrica*, 2002, 70 (3), 1007–1033.
- \_\_\_ and \_\_\_, “Information in mechanism design,” 2006.
- Bhattacharya, Sourav, John Duffy, and Sun-Tak Kim**, “Voting with Endogenous Information Acquisition: Theory and Evidence,” 2015. Manuscript, Wuhan University.
- Budish, Eric**, “The Combinatorial Assignment Problem: Approximate Competitive Equilibrium from Equal Incomes,” *Journal of Political Economy*, 2011, 119 (6), 1061–1103.
- Calsamiglia, Caterina, Guillaume Haeringer, and Flip Klijn**, “Constrained School Choice: An Experimental Study,” *American Economic Review*, September 2010, 100 (4), 1860–74.
- Chade, Hector, Gregory Lewis, and Lones Smith**, “Student Portfolios and the College Admissions Problem,” *The Review of Economic Studies*, 2014, 81 (3), 971–1002.
- Chen, Yan and Tayfun Sönmez**, “School Choice: An Experimental Study,” *Journal of Economic Theory*, 2006, 127, 202–231.
- Choi, Syngjoo, José-Alberto Guerra, and Jinwoo Kim**, “Interdependent Value Auctions with Insider Information: Theory and Experiment,” 2015.
- Compte, Olivier and Philippe Jehiel**, “Auctions and information acquisition: sealed bid or dynamic formats?,” *The RAND Journal of Economics*, 2007, 38 (2), 355–372.
- Crémer, Jacques and Fahad Khalil**, “Gathering Information before Signing a Contract,” *The American Economic Review*, 1992, 82 (3), 566–578.
- \_\_\_, \_\_\_, and **Jean-Charles Rochet**, “Strategic Information Gathering before a Contract Is Offered,” *Journal of Economic Theory*, 1998, 81 (1), 163–200.
- Crémer, Jacques, Yossi Spiegel, and CharlesZ Zheng**, “Auctions with costly information acquisition,” *Economic Theory*, 2009, 38 (1), 41–72.
- Dang, Tri Vi**, “Bargaining with endogenous information,” *Journal of Economic Theory*, 2008, 140 (1), 339–354.
- De Haan, Monique, Pieter A Gautier, Hessel Oosterbeek, and Bas Van der Klaauw**, “The

- performance of school assignment mechanisms in practice,” Technical Report, CEPR Discussion Papers 2015.
- Ding, Tingting and Andrew Schotter**, “Learning and Mechanism Design: An Experimental Test of School Matching Mechanisms With Intergenerational Advice,” 2015. New York University Manuscript.
- \_\_\_ and \_\_\_, “Matching and Chatting: An Experimental Study of the Impact of Network Communication on School-Matching Mechanisms,” 2015. New York University Manuscript.
- Dubins, Lester E. and Deborah A. Freedman**, “Machiavelli and the Gale-Shapley Algorithm,” *American Mathematical Monthly*, 1981, 88, 485–494.
- Dur, UM, Robert G Hammond, and Thayer Morrill**, “Identifying the Harm of Manipulable School-Choice Mechanisms,” Technical Report 2015.
- Dustan, Andrew**, “Peer Networks and School Choice under Incomplete Information,” *Unpublished manuscript*, 2015.
- \_\_\_, **Alain de Janvry, and Elisabeth Sadoulet**, “Flourish or Fail? The Risky Reward of Elite High School Admission in Mexico City,” *Unpublished manuscript*, 2015.
- Featherstone, Clayton and Muriel Niederle**, “Ex ante efficiency in school choice mechanisms: an experimental investigation,” 2008. Working Paper.
- Fischbacher, Urs**, “z-Tree: Zurich Toolbox for Ready-made Economic Experiment,” *Experimental Economics*, 2007, 10 (2), 171–178.
- Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen Weinberg**, “Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model,” *The American Economic Review*, 2006, 96 (4), 1043–1068.
- Gale, David and Lloyd S. Shapley**, “College Admissions and the Stability of Marriage,” *American Mathematical Monthly*, 1962, 69, 9–15.
- Gerardi, Dino and Leat Yariv**, “Information acquisition in committees,” *Games and Economic Behavior*, 2008, 62 (2), 436–459.
- Golman, Russell and George Loewenstein**, “The Demand For, and Avoidance of, Information,” 2015. Carnegie Mellon University Working Paper.
- Grant, Simon, Atsushi Kajii, and Ben Polak**, “Intrinsic Preference for Information,” *Journal of Economic Theory*, 1998, 83 (2), 233 – 259.
- Guillen, Pablo and Alexander Hing**, “Lying through their teeth: Third party advice and truth telling in a strategy proof mechanism,” *European Economic Review*, 2014, 70, 178 – 185.
- Harless, Patrick and Vikram Manjunath**, “The Importance of Learning in Market Design,”

2015.

**Hastings, Justine S. and Jeffrey M. Weinstein**, “Information, School Choice, and Academic Achievement: Evidence from Two Experiments,” *The Quarterly Journal of Economics*, 2008, 123 (4), 1373–1414.

**Hauswald, Robert and Robert Marquez**, “Competition and Strategic Information Acquisition in Credit Markets,” *Review of Financial Studies*, 2006, 19 (3), 967–1000.

**He, Yinghua**, “Gaming the Boston School Choice Mechanism in Beijing,” December 2014.

\_\_\_, **Antonio Miralles, Marek Pycia, and Jianye Yan**, “A Pseudo-Market Approach to Allocation Problems with Priorities,” *Mimeo*, 2015.

**Hossain, Tanjim and Ryo Okui**, “The Binarized Scoring Rule,” *The Review of Economic Studies*, 2013, 80 (3), 984–1001.

**Hoxby, Caroline and Christopher Avery**, “The Missing “One-offs”: The hidden supply of high-achieving, low-income students,” *Brookings papers on economic activity*, 2013, pp. 1–50.

\_\_\_ **and Sarah Turner**, “Expanding college opportunities for high-achieving, low income students,” *Stanford Institute for Economic Policy Research Discussion Paper*, 2013, (12-014).

\_\_\_ **and** \_\_\_, “What High-Achieving Low-Income Students Know About College,” Working Paper 20861, National Bureau of Economic Research January 2015.

**Hylland, Aanund and Richard Zeckhauser**, “The Efficient Allocation of Individuals to Positions,” *Journal of Political Economy*, 1979, 87 (2), 293–314.

**Kim, Jinwoo**, “The value of an informed bidder in common value auctions,” *Journal of Economic Theory*, 2008, 143 (1), 585–595.

**Klijn, Flip, Joana Pais, and Marc Vorsatz**, “Preference intensities and risk aversion in school choice: a laboratory experiment,” *Experimental Economics*, 2012, pp. 1–22.

**Lee, Robin S. and Michael Schwarz**, “Interviewing in Two-Sided Matching Markets,” *Mimeo*, 2012.

**Lester, Benjamin, Nicola Persico, and Ludo Visschers**, “Information Acquisition and the Exclusion of Evidence in Trials,” *Journal of Law, Economics, and Organization*, 2009.

**Nieuwerburgh, Stijn Van and Laura Veldkamp**, “Information Acquisition and Under-Diversification,” *The Review of Economic Studies*, 2010, 77 (2), 779–805.

**Pais, Joana, Ágnes Pintér, and Róbert F Veszteg**, “College Admissions and the Role of Information: An Experimental Study,” *International Economic Review*, 2011, 52 (3), 713–737.

\_\_\_ **and Ágnes Pintér**, “School choice and information: An experimental study on matching mechanisms,” *Games and Economic Behavior*, 2008, 64 (1), 303 – 328.

- Pathak, Parag A. and Tayfun Sönmez**, “Leveling the playing field: sincere and sophisticated players in the Boston mechanism,” *American Economic Review*, September 2008, 98, 1636–1652(17).
- Persico, Nicola**, “Information Acquisition in Auctions,” *Econometrica*, 2000, 68 (1), 135–148.
- \_\_\_, “Committee Design with Endogenous Information,” *The Review of Economic Studies*, 2004, 71 (1), 165–191.
- Prothero, Arianna**, “Parents Confront Obstacles as School Choice Expands,” *Education Week*, 2015, 34 (18), 1–16.
- Rastegari, Baharak, Anne Condon, and Nicole Immorlica**, “Two-sided matching with partial information,” in “In Proc. 14th ACM Conference on Electronic Commerce (EC13” 2013.
- Roth, Alvin E.**, “The Economics of Matching: Stability and Incentives,” *Mathematics of Operations Research*, 1982, 7, 617–628.
- \_\_\_ and **Marilda A. O. Sotomayor**, *Two-Sided Matching: A Study in Game-Theoretic Modeling and Analysis*, Cambridge: Cambridge University Press, 1990.
- Schotter, Andrew and Isabel Trevino**, “Belief Elicitation in the Lab,” 2013. New York University Manuscript.
- Shi, Xianwen**, “Optimal auctions with information acquisition,” *Games and Economic Behavior*, 2012, 74 (2), 666–686.
- Troyan, Peter**, “Comparing school choice mechanisms by interim and ex-ante welfare,” *Games and Economic Behavior*, 2012, 75 (2), 936–947.

Appendix for  
Information Acquisition and Provision in School Choice

Yan Chen

Yinghua He

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## Appendix A Omitted Proofs

Before proving the propositions, let us summarize the properties of the two mechanisms. As the results can be easily verified by going through the mechanisms, we thus omit the formal proof.<sup>13</sup>

**Lemma 2.** *DA and IA (with single tie breaking) have the following properties:*

(i) *Monotonicity: If the only difference between  $L_i$  and  $L'_i$  is that the position of  $s \in S \setminus \{s^0\}$  and  $t$  are swapped such that  $tL_i s$ ,  $sL'_i t$ ,  $sL'_i s^0$ , and  $\#\{s'' \in S | s' L_i s''\} = \#\{s'' \in S | s' L'_i s''\}$  for all  $s' \in S \setminus \{s, t\}$ , then:*

$$a_s(L'_i, L_{-i}) \geq a_s(L_i, L_{-i}), \forall L_{-i};$$

*and the inequality is strict when  $L_j = L_i$ ,  $\forall j \neq i$  and there exists  $s^* \in S \setminus \{s^0, s, t\}$  such that  $s^* L_i s^0$ .*

(ii) *Guaranteed share in first choice: If school  $s \in S \setminus \{s^0\}$  is top ranked in  $L_i$  by  $i$ ,  $a_s(L_i, L_{-i}) \geq q_s / |I|$ , for all  $L_{-i}$ .*

(iii) *Guaranteed assignment:  $\sum_{s \in \{s \in S | s L_i s^0\}} a_s(L_i, L_{-i}) + a_{s^0}(L_i, L_{-i}) = 1$  for all  $L_{-i}$ .*

### A.1 Proof of Lemma 1.

The proof applies to either DA or IA. Note that given any  $(\alpha_{-i}, \beta_{-i})$  of other students,  $\sigma^*(\omega)$  exists. This can be proven by the usual fixed point argument. Note that  $\sigma^*(\omega)$  does not depend on one's own investments in information acquisition, although it depends on the signal that one has received ( $\omega$ ).

Given  $\omega$ ,  $i$ 's payoff function can be written as:

$$\int \int \int u_i(V, \sigma, \sigma^*(\omega_{-i})) dF(V|\omega) dF(V_{-i}|\omega_{-i}) dH(\omega_{-i}|\alpha_{-i}, \beta_{-i}),$$

which is continuous in  $\sigma$ . Therefore, the value function  $\Pi(\omega, \alpha_{-i}, \beta_{-i})$  is continuous in  $(\alpha_{-i}, \beta_{-i})$  by the maximum theorem.

For student  $i$ , the optimal information acquisition is solved by the first-order conditions (second-order conditions are satisfied by the assumptions on the functions  $a()$ ,  $b()$ , and  $c()$ ):

$$\begin{aligned} a'(\alpha^*) \int & \left[ b(\beta^*(P)) \int \Pi((P, V), \alpha_{-i}^*, \beta_{-i}^*) F(V|P) \right. \\ & \left. + (1 - b(\beta^*(P))) \int \Pi((P, V^\phi), \alpha_{-i}^*, \beta_{-i}^*) - c(\alpha^*, \beta^*(P)) \right] dG(P|F) \\ & - a'(\alpha^*) [\Pi(P^\phi, \alpha_{-i}^*, \beta_{-i}^*) - c(\alpha^*, 0)] \\ & - a(\alpha^*) \int c_\alpha(\alpha^*, \beta^*(P)) dG(P|F) - (1 - a(\alpha^*)) c_\alpha(\alpha^*, 0) = 0 \end{aligned}$$

$$b'(\beta^*(P)) \left[ \int \Pi(V, \alpha_{-i}^*, \beta_{-i}^*) dF(V|P) - \Pi(P, \alpha_{-i}^*, \beta_{-i}^*) \right] - c_{\beta^*}(\alpha^*, \beta^*(P)) = 0, \forall P \in \mathcal{P}.$$

<sup>13</sup>Similar results on IA and their proofs are available in He (2014).

Given the non-negative value of information and the properties of  $a()$ ,  $b()$ , and  $c()$ , one can verify that there must exist  $\alpha^*$  and  $\beta^*(P)$  for all  $P \in \mathcal{P}$  such that the first-order conditions are satisfied.

## A.2 Proof of Proposition 1.

### A.2.1 Proof of $\alpha^* > 0$

Given the existence of a symmetric equilibrium, let us suppose instead that  $\alpha^* = 0$ . It implies that  $\beta^*(P) = 0$  for all  $P \in \mathcal{P}$  and that the value function can be simplified as:

$$\begin{aligned} \Pi(\omega, \alpha^*, \beta^*) &= \Pi((P^\phi, V^\phi), 0, \mathbf{0}) \\ &= \max_{\sigma} \left\{ \int \int u_i(V, \sigma, \sigma^*(\omega_{-i})) dF(V) dF(V_{-i}) \right\}. \end{aligned}$$

Since  $\alpha^* = 0$  and  $\beta^* = \mathbf{0}$  (a  $|\mathcal{P}|$ -dimensional vector of zeros) is a best response for  $i$ ,  $\forall \alpha > 0$ ,

$$\begin{aligned} &\Pi((P^\phi, V^\phi), 0, \mathbf{0}) \\ &\geq \left\{ a(\alpha) \int \Pi((P, V^\phi), 0, \mathbf{0}) dG(P|F) + (1 - a(\alpha)) \Pi((P^\phi, V^\phi), 0, \mathbf{0}) - c(\alpha, 0) \right\}; \end{aligned}$$

or

$$c(\alpha, 0) \leq a(\alpha) \left[ \int \Pi((P, V^\phi), 0, \mathbf{0}) dG(P|F) - \Pi((P^\phi, V^\phi), 0, \mathbf{0}) \right], \forall \alpha > 0,$$

which can only be satisfied if and only if  $\Pi((P, V^\phi), 0, \mathbf{0}) = \Pi((P^\phi, V^\phi), 0, \mathbf{0})$  for all  $P \in \mathcal{P}$ , given that  $\int \Pi((P, V^\phi), 0, \mathbf{0}) dG(P|F) \geq \Pi((P^\phi, V^\phi), 0, \mathbf{0})$  and  $c'(0, 0) < a'(0) = \infty$ .

Suppose that in a given symmetric equilibrium  $\sigma^*$ , the finiteness of the strategy space implies that in the equilibrium pure strategies  $(L^{(1)}, \dots, L^{(N)})$  are played with positive probabilities  $(p^{(1)}, \dots, p^{(N)})$  ( $N \in \mathbb{N}$ ).  $s^*$  is ranked the last in  $L^{(1)}$  among non-outside-option schools, i.e.,  $\#\{s \in S | s^* L^{(1)} s, s \neq s^0\} = 0$  and there is at least another school  $s_1$  s.t.  $s_1 L^{(1)} s^0$  and  $s_1 L^{(1)} s^*$ . Given the full support of ordinal preferences and Lemma 2, such an  $L^{(1)}$  must exist (otherwise, it cannot be an equilibrium). Similarly, there exists an ordinal preference  $P^*$  such that  $s^* P^* s^0 P^* s$  for all  $s \neq s^*, s^0$ .

Since  $\Pi((P^*, V^\phi), 0, \mathbf{0}) = \Pi((P, V^\phi), 0, \mathbf{0})$ , it implies that  $L^{(1)}$  is also a best response to  $\sigma^*$  even if  $i$  has learned  $P_i = P^*$ . We then compare  $i$ 's payoffs from submitting  $L^{(1)}$  and  $P^*$ .

By monotonicity of the mechanism (Lemma 2),  $a_{s^*}(P^*, L_{-i}) \geq a_{s^*}(P, L_{-i})$  for all  $L_{-i}$ , where  $P$  does not top rank  $s^*$ . Moreover,  $a_{s^*}(P^*, L_{-i}) > a_{s^*}(P, L_{-i})$  when everyone else submits  $L^{(1)}$  in  $L_{-i}$ .

$\sigma^*$  leads to a probability distribution over a finite number of possible profiles of other's strategies  $(L_{-i})$ . With a positive probability, everyone else plays  $L^{(1)}$ . In this event, therefore, by submitting  $P^*$ ,  $i$  strictly increases the probability of being accepted by  $s^*$ , the only acceptable school, comparing with that of submitting  $L^{(1)}$ . Furthermore, in any other possible profile of  $L_{-i}$ , the probability of being assigned to  $s^*$  is also always weakly higher when submitting  $P^*$ . Hence,

$L^{(1)}$  is not a best response to  $\sigma^*$  when  $P_i = P^*$ , and thus  $\Pi((P^*, V^\phi), 0, \mathbf{0}) \neq \Pi((P, V^\phi), 0, \mathbf{0})$ .

This contradiction proves that  $\alpha^* = 0$  is not an equilibrium. Since an equilibrium always exists, it must be that  $\alpha^* > 0$ .

### A.2.2 Proof of $\beta^*(P) = 0$ under DA

Suppose  $\beta^*(P) > 0$  for some  $P \in \mathcal{P}$  under DA or any strategy-proof ordinal mechanism. It implies that:

$$\beta^*(P) \int \Pi((P, V), \alpha_{-i}^*, \beta_{-i}^*) dF(V|P) + (1 - \beta^*(P)) \Pi((P, V^\phi), \alpha_{-i}^*, \beta_{-i}^*) - c(\alpha^*, \beta^*(P)) > \Pi((P, V^\phi), \alpha_{-i}^*, \beta_{-i}^*),$$

or,

$$\beta^*(P) \left[ \int \Pi((P, V), \alpha_{-i}^*, \beta_{-i}^*) dF(V|P) - \Pi((P, V^\phi), \alpha_{-i}^*, \beta_{-i}^*) \right] > c(\alpha^*, \beta^*(P)). \quad (2)$$

However, strategy-proofness implies that:

$$\int \Pi((P, V), \alpha_{-i}^*, \beta_{-i}^*) dF(V|P) = \Pi((P, V^\phi), \alpha_{-i}^*, \beta_{-i}^*),$$

and thus Equation (2) cannot be satisfied. Therefore  $\beta^*(P) = 0$  for all  $P \in \mathcal{P}$ .

### A.2.3 Proof of $\beta^*(P) > 0$ for some $P$ under IA

We construct an example where  $\beta^*(P) > 0$  for some  $P$  given the distribution  $F$  under IA. Suppose that  $F$  implies a distribution of ordinal preferences  $G(P|F)$  such that for  $s_1$  and  $s_2$ :

$$G(P|F) = \begin{cases} (1 - \varepsilon) & \text{if } P = \bar{P}, \text{ s.t. } s_1 \bar{P} s_2 \bar{P} s^0 \bar{P} s_3 \dots \bar{P} s_{|S|}; \\ \frac{\varepsilon}{|\mathcal{P}| - 1} & \text{if } P \neq \bar{P}. \end{cases}$$

The distribution of cardinal preferences is:

$$F(V|\bar{P}) = \begin{cases} 1 - \eta & \text{if } (v_{s_1}, v_{s_2}, v_{s^0}) = (1, \xi, \xi/2) \text{ and } v_s < v_{s^0}, \forall s \in S \setminus \{s_1, s_2, s^0\}; \\ \eta & \text{if } (v_{s_1}, v_{s_2}, v_{s^0}) = (1, 1 - \xi, \xi/2) \text{ and } v_s < v_{s^0}, \forall s \in S \setminus \{s_1, s_2, s^0\}; \\ 0 & \text{otherwise.} \end{cases}$$

$(\varepsilon, \eta, \xi)$  are all small positive numbers in  $(0, 1)$ . Otherwise, there is no restriction on  $F(V|P)$  for  $P \neq \bar{P}$  nor on  $v_s, \forall s \in S \setminus \{s_1, s_2, s^0\}$ .

Suppose that  $\beta^*(P) = 0$  for all  $P \in \mathcal{P}$ . If  $\omega_i = (\bar{P}, V^\phi)$  (i.e., ordinal preferences are known

but not cardinal ones), the expected payoff of being assigned to  $s_2$  is:

$$E(v_{i,s_2}|\bar{P}) = (1 - \eta)\xi + \eta(1 - \xi).$$

And  $(\eta, \xi)$  are small enough such that  $E(v_{i,s_2}|\bar{P}) < q_{s_1}/|I|$ , and therefore obtaining  $s_2$  for sure is less preferable than obtaining  $q_{s_1}/|I|$  of  $s_1$ . In equilibrium with such small enough  $(\varepsilon, \eta, \xi)$ , it must be that:

$$\sigma^*((\bar{P}, V^\phi), \alpha^*, \mathbf{0}) = \sigma^*((P^\phi, V^\phi), \alpha^*, \mathbf{0}) = \bar{P}.$$

Therefore, from  $i$ 's perspective, any other player,  $j$ , plays  $\bar{P}$  with probability:

$$(1 - a(\alpha^*)) + a(\alpha^*)(1 - \varepsilon) > 1 - \varepsilon.$$

It then suffices to show that some students deviate from such equilibrium strategies. Suppose that  $i$  had learned her ordinal preferences and  $P_i = \bar{P}$ . If furthermore she succeeds in acquiring information on  $V_i$ , there is a positive probability that  $(v_{s_1}, v_{s_2}, v_{s_0}) = (1, 1 - \xi, \xi/2)$ . In this case, if she plays  $L_i$  s.t.,  $s_2 L_i s_1 L_i s^0 L_i s_3 \dots L_i s_{|S|}$  (or other payoff-equivalent strategies), her expected payoff is at least:

$$(1 - \xi)(1 - \varepsilon)^{(|I|-1)},$$

While playing  $P_i (= \bar{P})$  leads to an expected payoff less than:

$$(1 - \varepsilon)^{(|I|-1)} \left[ \frac{q_{s_1}}{|I|} + \left(1 - \frac{q_{s_1}}{|I|}\right) \frac{\xi}{2} \right] + \left(1 - (1 - \varepsilon)^{(|I|-1)}\right).$$

This upper bound is obtained under the assumption that one is always assigned to  $s_1$  when not everyone submits  $\bar{P}$ . When  $(\varepsilon, \xi)$  are close to zero, it is strictly profitable to submit  $L_i$  instead of  $\bar{P}$ :

$$\int \Pi((\bar{P}, V), \alpha_{-i}^*, \mathbf{0}) dF(V|\bar{P}) > \Pi((\bar{P}, V^\phi), \alpha_{-i}^*, \mathbf{0}),$$

because in other realizations of  $V$ ,  $i$  cannot do worse than submitting  $\bar{P}$ . The marginal payoff of increasing  $\beta(\bar{P})$  from zero by  $\Delta$  is then:

$$\Delta \left( b'(0) \left[ \int \Pi((\bar{P}, V), \alpha_{-i}^*, \mathbf{0}) dF(V|\bar{P}) - \Pi((\bar{P}, V^\phi), \alpha_{-i}^*, \mathbf{0}) \right] - c_\beta(\alpha^*, 0) \right),$$

which is strictly positive given  $c_\beta(\alpha^*, 0) < b'(0) = +\infty$ . This proves that under IA  $\beta^*(P) > 0$  for some  $P \in \mathcal{P}$  given  $F$ .

### A.3 Proof of Proposition 2.

For the first part, by the definition of strategy-proofness, information on others' types does not change one's best response. Therefore,  $\delta^*(V) = 0$  for all  $V$  under any strategy-proof mechanism.

To prove the second part, we construct an example of  $F(V)$  to show  $\delta^*(V) > 0$  for some  $V$  under IA:

$$F(V) = \begin{cases} \frac{1}{2} - \varepsilon & \text{if } V = V^{(1)} \text{ s.t. } (v_{s_1}, v_{s_2}, v_{s^0}) = (1, 0, \xi), v_s \in (0, \xi) \forall s \notin \{s_1, s_2, s^0\}; \\ \frac{1}{2} - \varepsilon & \text{if } V = V^{(2)} \text{ s.t. } (v_{s_1}, v_{s_2}, v_{s^0}) = (0, 1, \xi), v_s \in (0, \xi) \forall s \notin \{s_1, s_2, s^0\}; \\ \varepsilon & \text{if } V = V^{(3)} \text{ s.t. } (v_{s_1}, v_{s_2}, v_{s^0}) = (1, 1 - \eta, \xi), v_s \in (0, \xi) \forall s \notin \{s_1, s_2, s^0\}; \end{cases}$$

where  $(\varepsilon, \xi, \eta)$  are small positive values. Besides,  $F(V \in [0, 1]^{|S|} \setminus \{V^{(1)}, V^{(2)}, V^{(3)}\}) = \varepsilon$ .

Suppose that for student  $i$ ,  $V_i = V^{(3)}$ . If  $\delta^*(V) = 0$  for all  $V$ , the best response for  $i$  in equilibrium is  $P_i$  or  $L_i$  s.t.  $s_2 L_i s_1 L_i s^0 L_i s$  for all other  $s$ . Without knowing  $V_{-i}$ ,  $i$  has to play a pure strategy,  $P_i$  or  $L_i$ , or a mixed strategy  $\Delta(\{P_i, L_i\})$  in equilibrium.  $\delta^*(V_i) = 0$  implies that either the two pure strategies are always payoff-equivalent or one always dominates the other, given any realization of  $V_{-i}$ .

Given  $F(V)$ , there is a positive probability,  $(\frac{1}{2} - \varepsilon)^{|I|-1}$ , that every other student has  $V^{(1)}$  and submit her true preferences. In this case, the payoff for  $i$  submitting  $P_i$  is less than  $q_{s_1}/|I| + \xi$ , while the one when submitting  $L_i$  is  $(1 - \eta)$ .

There is also a positive probability,  $(\frac{1}{2} - \varepsilon)^{|I|-1}$ , that every other student has  $V^{(2)}$  and submit her true preferences. In this case, the payoff for  $i$  submitting  $P_i$  is 1, while the one when submitting  $L_i$  is at most  $(1 - \eta)q_{s_1}/|I| + \xi$ .

Since  $\int \Phi(V, V_{-i}, \delta_{-i}^*) dF(V_{-i}) \geq \Phi(V, V_{-i}^\phi, \delta_{-i}^*)$  and the above shows they are different for some realization of  $(V_i, V_{-i})$ , thus:

$$\int \Phi(V, V_{-i}, \delta_{-i}^*) dF(V_{-i}) - \Phi(V, V_{-i}^\phi, \delta_{-i}^*) > 0.$$

The marginal payoff of acquiring information (increasing  $\delta(V_i)$  from zero to  $\Delta$ ) is:

$$\Delta \left( d'(0) \left[ \int \Phi(V, V_{-i}, \delta_{-i}^*) dF(V_{-i}) - \Phi(V, V_{-i}^\phi, \delta_{-i}^*) \right] - e'(0) \right),$$

which is positive for small  $(\varepsilon, \xi, \eta)$  because  $e'(0) < d'(0) = \infty$ . This proves that  $\delta^*(V) > 0$  for some  $V$  with a positive measure given  $F$ .

### A.4 Proof of Proposition 3.

Under UI, the only information  $i$  has is that her preferences follow the distribution  $F(V)$ . Denote  $W_i^E$  as the expected (possibly weak) ordinal preferences of  $i$  such that  $s W_i^E t$  if and only if  $\int v_{i,s} dF_{v_s}(v_{i,s}) \geq \int v_{i,t} dF_{v_t}(v_{i,t})$ . Given  $W_i^E, (P_i^{E,1}, \dots, P_i^{E,M}) \in \mathcal{P}$  are all the strict ordinal

preferences that can be generated by randomly breaking ties in  $W_i^E$  if there is any. Therefore,  $M \geq 1$ .

When others play  $L_{-i}$ , the expected payoff of  $i$  playing  $L_i$  is:

$$\int \sum_{s \in S} a_s(L_i, L_{-i}) v_{i,s} dF(V) = \sum_{s \in S} a_s(L_i, L_{-i}) \int v_{i,s} dF_{v_s}(v_{i,s}).$$

Since DA with single tie breaking is essentially the random serial dictatorship, it is therefore a dominant strategy that  $i$  submits any  $P_i^{E,m}$   $m \in \{1, \dots, M\}$ . Moreover, a strategy that is not in  $(P_i^{E,1}, \dots, P_i^{E,M})$  can never be played in any equilibrium, because there is a positive-measure set of realizations of the lottery that such a strategy leads to a strictly positive loss.

We claim that in equilibrium for any  $L_{-i}^*$  such that  $L_j^* \in (P_i^{E,1}, \dots, P_i^{E,M})$ ,  $j \neq i$ , the payoff to  $i$  is:

$$\sum_{s \in S} a_s(P_i^{E,m}, L_{-i}^*) \int v_{i,s} dF_{v_s}(v_{i,s}) = \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}), \forall m. \quad (3)$$

Note that for any  $L_{-i}^*$ ,  $\sum_{s \in S} a_s(P_i^{E,m}, L_{-i}^*) \int v_{i,s} dF_{v_s}(v_{i,s})$  does not vary across  $m$  given that any  $P_i^{E,m}$  is a dominant strategy.

Since everyone has the same expected utility of being assigned to every school, the maximum utilitarian sum of expected utility is:

$$\sum_{s \in S \setminus \{s^0\}} q_s \int v_{i,s} dF_{v_s}(v_{i,s}) \quad (4)$$

If Equation (3) is not satisfied and there exists  $i$  such that for some  $\hat{L}_{-i}^*$ :

$$\sum_{s \in S} a_s(P_i^{E,m}, \hat{L}_{-i}^*) \int v_{i,s} dF_{v_s}(v_{i,s}) > \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}), \forall m. \quad (5)$$

The maximum utilitarian social welfare in (4) implies that there exists  $j \in I \setminus \{i\}$  and  $m \in \{1, \dots, M\}$  such that:

$$\sum_{s \in S} a_s(P_j^{E,m}, \hat{L}_{-j}^*) \int v_{j,s} dF_{v_s}(v_{j,s}) < \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{j,s} dF_{v_s}(v_{j,s}), \quad (6)$$

where  $P_j^{E,m}$  is  $j$ 's strategy in  $\hat{L}_{-i}^*$  and  $P_j^{E,m} = P_i^{E,m}$ . We can always find such  $P_i^{E,m}$  and  $P_j^{E,m}$  because condition (5) is satisfied for all  $m$ . However, the even lottery implies that:

$$a_s(P_i^{E,m}, (L_{-(i,j)}^*, P_j^{E,m})) = a_s(P_j^{E,m}, (L_{-(i,j)}^*, P_i^{E,m})) \quad \forall s \text{ if } P_i^{E,m} = P_j^{E,m},$$

and thus:

$$\sum_{s \in S} a_s \left( P_j^{E,m}, \left( L_{-(i,j)}^*, P_i^{E,m} \right) \right) \int v_{j,s} dF_{v_s}(v_{j,s}) = \sum_{s \in S} a_s \left( P_i^{E,m}, \left( L_{-(i,j)}^*, P_j^{E,m} \right) \right) \int v_{i,s} dF_{v_s}(v_{i,s}),$$

which contradicts the inequalities (5) and (6). This proves (3) is always satisfied.

Under OI, CI, or PI, the unique equilibrium is for everyone to report the true ordinal preferences, and thus the expected payoff (ex ante) is:

$$\begin{aligned} & \int \int \sum_{s \in S} a_s(P, L_{-i}(P)) v_{i,s} dF(V|P) dG(P|F) \\ &= \int \int \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} v_{i,s} dF_{v_s}(v_{i,s}|P) dG(P|F) \\ &= \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}), \end{aligned}$$

where  $L_{-i}(P)$  is such that that  $L_j = P, \forall j \in I \setminus \{i\}$ .

## A.5 Proof of Proposition 4.

### A.5.1 Welfare under UI and OI

We first show UI = OI in symmetric equilibrium in terms of *ex ante* student welfare.

Under UI, the game can be transformed into one similar to PI but everyone has the same cardinal preferences that are represented in terms of the expected utilities  $\left[ \int v_{i,s} dF_{v_s}(v_{i,s}) \right]_{s \in S}$ . In a symmetric equilibrium, everyone thus must play exactly the same strategy, either pure or mixed, which further implies that everyone is assigned to each school with the same probability and has the same *ex ante* welfare:

$$\sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}).$$

Under OI, everyone knows that everyone has the same ordinal preferences  $P$ . The game again can be considered as one under PI where everyone has the same cardinal preferences,  $\left[ \int v_{i,s} dF_{v_s}(v_{i,s}|P) \right]_{s \in S}$ . Similar to the argument above, the payoff conditional on  $P$  is:

$$\sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}|P),$$

which leads to an *ex ante* payoff:

$$\int \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}|P) dG(P|F) = \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}).$$

### A.5.2 Proof of $CI \geq UI = OI$ under IA

We then show  $CI \geq OI = UI$ .

Under CI, everyone's cardinal preferences  $V_i$  are her private information, although her ordinal preferences  $P$ , which is common across  $i$ , are common knowledge. Suppose that  $\sigma^{BN}(V) : [0, 1]^{|S|} \rightarrow \Delta(\mathcal{P})$  is a symmetric Bayesian Nash equilibrium. We show that:

$$\begin{aligned} & \int \int \left( \int A(\sigma^{BN}(V_i), \sigma^{BN}(V_{-i})) dF(V_{-i}|P) \cdot V_i \right) dF(V_i|P) dG(P|F) \\ & \geq \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}). \end{aligned}$$

The following uses the same idea as in the proof of Proposition 2 in (Trojan 2012). Note that  $\int a_s(\sigma^{BN}(V_i), \sigma^{BN}(V_{-i})) dF(V_{-i}|P)$  is  $i$ 's probability of being assigned to  $s$  in equilibrium when the realization of cardinal preferences is  $V_i$ . Furthermore, the *ex ante* assignment probability, i.e., the probability before the realization of  $P$  and  $V_i$ , is

$$\int \int \int a_s(\sigma^{BN}(V_i), \sigma^{BN}(V_{-i})) dF(V_{-i}|P) dF(V_i|P) dG(P|F),$$

which must be the same across students by symmetry. Therefore, we must have:

$$|I| \int \int \int a_s(\sigma^{BN}(V_i), \sigma^{BN}(V_{-i})) dF(V_{-i}|P) dF(V_i|P) dG(P|F) = q_s, \forall s \in S \setminus \{s^0\}, \quad (7)$$

as in equilibrium all seats at all  $s \in S \setminus \{s^0\}$  must be assigned.

Suppose  $i$  plays an alternative strategy  $\sigma_i$  such that  $\sigma_i = \int \int \sigma^{BN}(V_i) dF(V_i|P) dG(P|F) = \int \sigma^{BN}(V_i) dF(V_i)$ . That is,  $i$  plays the ‘‘average’’ strategy of the equilibrium strategy regardless of her preferences. Her payoff given any realization of  $P$  is:

$$\begin{aligned} & \int \left( \int A(\sigma_i, \sigma^{BN}(V_{-i})) dF(V_{-i}|P) \cdot V_i \right) dF(V_i|P) \\ & = \int \left( \int \left( \int \int A(\sigma^{BN}(V_i), \sigma^{BN}(V_{-i})) dF(V_i|P) dG(P|F) \right) dF(V_{-i}|P) \cdot V_i \right) dF(V_i|P) \\ & = \int \left( \sum_{s \in S} \left( \int \int \int a_s(\sigma^{BN}(V_i), \sigma^{BN}(V_{-i})) dF(V_i|P) dG(P|F) dF(V_{-i}|P) \right) v_{i,s} \right) dF(V_i|P) \\ & = \int \left( \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} v_{i,s} \right) dF(V_i|P). \end{aligned}$$

The last equation is due to (7). Since  $\sigma_i$  may not be optimal for  $i$  upon observing her preferences

$V_i$ , we thus have for *ex ante* welfare:

$$\begin{aligned} & \int \int \left( \int A(\sigma^{BN}(V_i), \sigma^{BN}(V_{-i})) dF(V_{-i}|P) \cdot V_i \right) dF(V_i|P) dG(P|F) \\ & \geq \int \int \left( \int A(\sigma_i, \sigma^{BN}(V_{-i})) dF(V_{-i}|P) \cdot V_i \right) dF(V_i|P) dG(P|F) \\ & = \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}), \end{aligned}$$

which proves  $CI \geq OI = UI$  in terms of Pareto dominance of *ex ante* student welfare.

### A.5.3 Proof of $PI \geq OI = UI$ under IA

Under PI, everyone's cardinal preferences  $V_i$  are common knowledge. Given a symmetric equilibrium, by the same argument as above, we must have PI Pareto dominates OI and UI.

Suppose that  $\sigma^{NE}(V_i, V_{-i}) : [0, 1]^{|S| \times |I|} \rightarrow \Delta(\mathcal{P})$  is a symmetric Nash equilibrium. We show that:

$$\begin{aligned} & \int \int \int \left( A(\sigma^{NE}(V_i, V_{-i}), [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}) \cdot V_i \right) dF(V_{-i}|P) dF(V_i|P) dG(P|F) \\ & \geq \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}). \end{aligned}$$

Note that  $a_s(\sigma^{NE}(V_i, V_{-i}), [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}})$  is  $i$ 's probability of being assigned to  $s$  in equilibrium when the realization of cardinal preferences is  $(V_i, V_{-i})$ . Furthermore, the *ex ante* assignment probability, i.e., the probability before the realization of  $P$  and  $(V_i, V_{-i})$ , is

$$\int \int \int a_s(\sigma^{NE}(V_i, V_{-i}), [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}) dF(V_{-i}|P) dF(V_i|P) dG(P|F),$$

which must be the same across students by symmetry. Therefore, we must have,  $\forall s \in S \setminus \{s^0\}$ :

$$|I| \int \int \int a_s(\sigma^{NE}(V_i, V_{-i}), [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}) dF(V_{-i}|P) dF(V_i|P) dG(P|F) = q_s, \quad (8)$$

as in equilibrium all seats at all  $s \in S \setminus \{s^0\}$  must be assigned.

Suppose  $i$  plays an alternative strategy  $\sigma_i$  such that

$$\sigma_i = \int \int \int \sigma^{NE}(V_i, V_{-i}) dF(V_{-i}|P) dF(V_i|P) dG(P|F).$$

That is,  $i$  plays the ‘‘average’’ strategy of the equilibrium strategy regardless of her and others’

preferences. Her payoff given a realization of  $(V_i, V_{-i})$  is:

$$\begin{aligned}
& A\left(\sigma_i, [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}\right) \cdot V_i \\
&= \left( \int \int \int A\left(\sigma^{NE}(V_i, V_{-i}), [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}\right) dF(V_{-i}|P) dF(V_i|P) dG(P|F) \right) \cdot V_i \\
&= \sum_{s \in S} \left( \int \int \int a_s\left(\sigma^{NE}(V_i, V_{-i}), [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}\right) dF(V_i|P) dG(P|F) dF(V_{-i}|P) \right) v_{i,s} \\
&= \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} v_{i,s}.
\end{aligned}$$

The last equation is due to (8). Therefore, her payoff given a realization of  $P$  is:

$$\begin{aligned}
& \int \int \left( A\left(\sigma_i, [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}\right) \cdot V_i \right) dF(V_{-i}|P) dF(V_i|P) \\
&= \int \left( \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} v_{i,s} \right) dF(V_i|P).
\end{aligned}$$

Since  $\sigma_i$  may not be optimal for  $i$  upon observing her and others' preferences  $(V_i, V_{-i})$ , we thus have:

$$\begin{aligned}
& \int \int \int \left( A\left(\sigma^{NE}(V_i, V_{-i}), [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}\right) \cdot V_i \right) dF(V_{-i}|P) dF(V_i|P) dG(P|F) \\
&\geq \int \int \int \left( A\left(\sigma_i, [\sigma^{NE}(V_j, V_{-j})]_{j \in I \setminus \{i\}}\right) \cdot V_i \right) dF(V_{-i}|P) dF(V_i|P) dG(P|F) \\
&= \sum_{s \in S \setminus \{s^0\}} \frac{q_s}{|I|} \int v_{i,s} dF_{v_s}(v_{i,s}),
\end{aligned}$$

which thus proves that  $PI > OI = UI$  in terms of Pareto dominance.

We use two examples to show part (iii) in Proposition 4: Section A.5.4 shows that PI can dominate CI in symmetric equilibrium; and the example in section A.5.5 shows the opposite.

#### A.5.4 Example: PI dominates CI in symmetric equilibrium under IA

There are 3 schools  $(a, b, c)$  and 3 students whose cardinal preferences are i.i.d. draws from the following distribution:

$$\begin{aligned}
\Pr((v_a, v_b, v_c) = (1, 0.1, 0)) &= 1/2 \\
\Pr((v_a, v_b, v_c) = (1, 0.5, 0)) &= 1/2
\end{aligned}$$

Each school has one seat. For any realization of preference profile, we can find a symmetric Nash equilibrium as in Table A1.

Realization of Preferences	Probability Realized	Strategy given realized type		Payoff given realized type	
		(1, 0.1, 0)	(1, 0.5, 0)	(1, 0.1, 0)	(1, 0.5, 0)
(1, 0.1, 0) (1, 0.1, 0) (1, 0.1, 0)	1/8	(a, b, c)	-	11/30	-
(1, 0.5, 0) (1, 0.1, 0) (1, 0.1, 0)	1/4	(a, b, c)	(b, a, c)	1/2	1/2
(1, 0.5, 0) (1, 0.5, 0) (1, 0.1, 0)	1/4	(a, b, c)	(a, b, c)	11/30	1/2
(1, 0.5, 0) (1, 0.5, 0) (1, 0.5, 0)	1/8	-	(a, b, c)	-	1/2

The above symmetric equilibrium leads to an *ex ante* student welfare:

$$\frac{1}{2} \left( \frac{11}{4 \cdot 30} + \frac{11}{2 \cdot 2} + \frac{11}{4 \cdot 30} \right) + \frac{1}{2} \left( \frac{11}{4 \cdot 2} + \frac{11}{2 \cdot 2} + \frac{11}{4 \cdot 2} \right) = \frac{14}{30}.$$

When everyone's preference is private information, we can verify that the unique symmetric Bayesian Nash equilibrium is that:

$$\sigma^{BN}((1, 0.1, 0)) = \sigma^{BN}((1, 0.5, 0)) = (a, b, c).$$

That is, everyone submits her true preference ranking. This leads to an *ex ante* welfare of:

$$\frac{11}{2 \cdot 30} + \frac{11}{2 \cdot 30} = \frac{11}{30}$$

which is lower than the above symmetric equilibrium under PI.

Also note that always playing  $(a, b, c)$  is also a symmetric Nash equilibrium under PI in all realizations of preference profile, which leads to the same *ex ante* student welfare as  $\sigma^{BN}$ .

#### A.5.5 Example: PI is dominated by CI in symmetric equilibrium under IA

There are 3 schools  $(a, b, c)$  and 3 students whose cardinal preferences are i.i.d. draws from the following distribution:

$$\begin{aligned} \Pr((v_a, v_b, v_c) = (1, 0.1, 0)) &= 3/4 \\ \Pr((v_a, v_b, v_c) = (1, 0.9, 0)) &= 1/4 \end{aligned}$$

Each school has one seat. For any realization of preference profile, we can find a symmetric Nash equilibrium as in Table A2. The *ex ante* welfare under PI with the above symmetric equilibrium profile is:

$$\frac{3}{4} \left( \frac{9}{16} \frac{11}{30} + \frac{6}{16} \frac{1}{2} + \frac{1}{16} \frac{3073}{3610} \right) + \frac{1}{4} \left( \frac{1}{16} \frac{19}{30} + \frac{6}{16} \frac{99}{190} + \frac{9}{16} \frac{9}{10} \right) = \frac{22549}{43320} \approx 0.52052.$$

Table A2: Symmetric Nash Equilibrium for Each Realization of the Game under PI

Realization of Preference	Probability Realized	Strategy given realized type		Payoff given realized type	
		(1, 0.1, 0)	(1, 0.9, 0)	(1, 0.1, 0)	(1, 0.9, 0)
(1, 0.1, 0) (1, 0.1, 0) (1, 0.1, 0)	27/64	(a, b, c)	-	11/30	-
(1, 0.9, 0) (1, 0.1, 0) (1, 0.1, 0)	27/64	(a, b, c)	(b, a, c)	1/2	9/10
(1, 0.9, 0) (1, 0.9, 0) (1, 0.1, 0)	9/64	(a, b, c)	(a, b, c) w/ prob 3/19 (b, a, c) w/ prob 16/19	3073/3610	99/190
(1, 0.9, 0) (1, 0.9, 0) (1, 0.9, 0)	1/64	-	(a, b, c) w/ prob 11/19 (b, a, c) w/ prob 8/19	-	19/30

Under CI, i.e., when one's own preferences are private information and the distribution of preferences is common knowledge, there is a symmetric Bayesian Nash equilibrium:

$$\sigma^{BN}((1, 0.9, 0)) = (b, a, c); \sigma^{BN}((1, 0.1, 0)) = (a, b, c).$$

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:

$$\frac{9}{16} \left( \frac{1}{3} \left( 1 + \frac{1}{10} + 0 \right) \right) + \frac{6}{16} \frac{1}{2} + \frac{1}{16} = \frac{219}{480}.$$

For a type-(1, 0.9, 0) student, given others follow  $\sigma^{BN}$ , playing  $(b, a, c)$  results in a payoff of:

$$\frac{9}{16} \frac{9}{10} + \frac{6}{16} \left( \frac{1}{2} \left( \frac{9}{10} + 0 \right) \right) + \frac{1}{16} \left( \frac{1}{3} \left( \frac{9}{10} + 1 + 0 \right) \right) = \frac{343}{480}.$$

If a type-(1, 0.9, 0) student deviates to  $(a, b, c)$ , she obtains:

$$\frac{9}{16} \left( \frac{1}{3} \left( \frac{9}{10} + 1 + 0 \right) \right) + \frac{6}{16} \left( \frac{1}{2} (1 + 0) \right) + \frac{1}{16} (1) = \frac{291}{480}.$$

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 ex ante payoff to every student in this equilibrium under CI is:

$$\frac{219}{480} \frac{3}{4} + \frac{343}{480} \frac{1}{4} = \frac{25}{48} \approx 0.52083,$$

which is higher than that under PI.

In this example, the reason that PI leads to lower welfare is because it sometimes leads to type-(1, 0.9, 0) students to play mixed strategies in equilibrium. Therefore, sometimes school B is assigned to a type-(1,0.1,0) student, which never happens under CI in symmetric Bayesian Nash equilibrium.

## Appendix B Analyses of Student Strategies (Rank-Ordered Lists) in the Experiment

This appendix investigates the effects of information provision and the effects of information acquisition on individual strategies. In Appendix E, we derive the equilibrium strategies under various information structure some of which are augmented with information acquisition.

The first information structure is UI (UnInformed: no one is informed about her valuation of school B), under which we have the following hypothesis based on our theoretical results.

**Hypothesis 9** (ROL: UI). *A risk neutral player submits a ROL of ABC as a dominant strategy under either IA or DA.*

**Result 5** (ROL: UI). *When subjects play the game under UI, 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 CI (Cardinally Informed: everyone is informed about her own valuation of school B but not others’ valuations).<sup>14</sup> Also note that under the treatment of OwnValue, one can acquire information on 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 10** (ROL: CI and Acquiring OwnValue). *When a subject knows her own preferences but does not know others’ preferences, it is a BNE (dominant strategy) to submit a ROL truthfully under IA (DA), regardless of the number of opponents who know their own preferences.*

**Result 6** (ROL: CI 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*

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<sup>14</sup>By design, in this experiment, CI is equivalent to OI (Ordinally Informed: everyone is informed of her ordinal preferences but not others).

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 that with free information (79%) ( $p$ -value = 0.01).

Lastly, we consider information structure PI (Perfectly Informed: 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 11** (ROL: PI 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 7** (ROL: PI 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 that with free information (91%). The difference is again insignificant ( $p$ -value = 0.86), partly because there are only 16 subjects successfully acquired 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).<sup>15</sup>*

We consider our above results to be consistent with the theoretical predictions. Moreover, the only incidence where costly acquired information and freely provided information have significant effects is that acquired information on OwnValue makes subjects more likely to play dominant strategy.

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<sup>15</sup>One may be tempted to investigate subjects' strategies conditional the preference profile of all subjects. This however makes the samples very small, especially among those who successfully acquired information (61 in total).

## Appendix C Additional Analyses of Experimental Data

In this appendix, we present the summary statistics of the experimental data (Table C3) and then focus on the robustness of our analyses in Section 5.1 on willingness to pay for information.

### C.1 Willingness to Pay for Information: Robustness of Results

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

Corresponding to Table 4 in Section 5.1, we present Table C4 where subject-average WTP is regressed on treatment types and other controls. The two sets of results are qualitatively the same.

In comparison with results from a random effect Tobit model in Tables 5 and 6, the next two tables investigate determinants of WTP in random and fixed effects panel regressions. In all specifications, our outcome variable is the subject-round WTP. Our specification is as follows:

$$WTP_{i,t} = \alpha_i + \beta_1 highB\_IA_{i,t} + \beta_2 highB\_DA_{i,t} + \beta_3 WTP\_Guess_{i,t} + \dots + Controls_{i,t} + \varepsilon_{i,t},$$

where  $i$  is the index for subjects and  $t$  for rounds (with each session);  $\alpha_i$  is subject fixed effects; and thus all control variables are time-subject-specific. Other controls are the same as in Section 5.1. Depending on the model being random effects or fixed effects, we have different interpretations of  $\alpha_i$ .

The endogeneity of  $WTP\_Guess_{i,t}$  is plausible if there are some common shocks in round  $t$  makes everyone's  $WTP_{i,t}$  and  $WTP\_Guess_{i,t}$  higher. We address this with an IV approach where the lagged  $WTP\_Guess_{i,t-1}$  is the instrumental variable. Clearly,  $WTP\_Guess_{i,t-1}$  is correlated with  $WTP\_Guess_{i,t}$ , as there might some persistence in one's guess of others WTP. Moreover, conditional on what others have done in the previous round,  $WTP\_Average_{i,t-1}$ , what  $i$  guessed in  $t - 1$  should not affect her decision in round  $t$  directly.

Fixed-effect results are shown in Table C5. The first three columns are from OLS regressions, while Column (4) is from an IV regression, where the instrument for the potentially endogenous variable,  $WTP\_Guess_{i,t}$ , is  $WTP\_Guess_{i,t-1}$ . Column (5) shows the first-stage result.

Comparing column (1) with column (2), the  $WTP\_guess$  explains 12% of the variations in WTP – excluding  $WTP\_guess$  decreases the R squared from 0.19 to 0.07. Besides, when  $WTP\_Guess_{i,t}$  is included  $WTP\_Guess_{i,t-1}$  has an insignificant coefficient both statistically and economically.

We then consider  $WTP\_Guess_{i,t-1}$  as an IV for use  $WTP\_Guess_{i,t}$ . Column (5) presents the first-stage result which shows that  $WTP\_Guess_{i,t-1}$  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 increased. We then perform an endogeneity test. Under the null hypothesis that  $WTP\_Guess_{i,t}$  can actually be treated as

Table C3: Summary Statistics

	Full Sample	Consistent Subjects in Holt-Laury Lottery Choice Game <sup>a</sup>				
		All Treatments	IA		DA	
			OwnValue	OtherValue	OwnValue	OtherValue
(1)	(2)	(3)	(4)	(5)	(6)	
WTP for info	4.43 (4.53)	4.29 (4.53)	6.45 (4.83)	4.28 (4.61)	4.29 (4.27)	1.89 (2.92)
Guess of others' WTP	5.20 (2.89)	5.15 (2.90)	7.06 (2.42)	5.38 (2.93)	4.61 (2.62)	3.41 (2.32)
Info Acquired	0.29 (0.45)	0.27 (0.45)	0.42 (0.49)	0.25 (0.44)	0.29 (0.45)	0.11 (0.32)
high_B×IA_OtherValue	0.05 (0.22)	0.05 (0.21)	- -	0.19 (0.39)	- -	- -
high_B×DA_OtherValue	0.05 (0.22)	0.05 (0.21)	- -	- -	- -	0.20 (0.40)
Wealth in each round	1143.38 (580.10)	1133.08 (573.57)	1105.27 (582.17)	1225.36 (554.35)	1068.56 (555.51)	1144.38 (591.76)
Wealth after all rounds	2063.19 (394.54)	2067.71 (400.08)	2037.93 (412.24)	2206.72 (362.63)	1963.48 (402.38)	2079.24 (388.82)
Misunderstanding DA	0.05 (0.11)	0.04 (0.10)	0.00 (0.00)	0.00 (0.00)	0.09 (0.14)	0.07 (0.12)
Costly-Free	0.50 (0.50)	0.52 (0.50)	0.54 (0.50)	0.47 (0.50)	0.53 (0.50)	0.51 (0.50)
Risk aversion	5.59 (2.80)	6.65 (1.43)	6.34 (1.24)	6.47 (1.54)	6.76 (1.45)	7.05 (1.41)
Consistent in Holt-Laury	0.84 (0.37)	- -	- -	- -	- -	- -
Curiosity	4.20 (4.95)	4.00 (4.89)	5.65 (5.45)	4.51 (5.08)	3.62 (4.58)	2.09 (3.43)
<i>Demographics</i>						
Female	0.54 (0.50)	0.53 (0.50)	0.44 (0.50)	0.56 (0.50)	0.55 (0.50)	0.58 (0.49)
Graduate student	0.45 (0.50)	0.44 (0.50)	0.51 (0.50)	0.38 (0.49)	0.40 (0.49)	0.47 (0.50)
Black	0.31 (0.46)	0.33 (0.47)	0.30 (0.46)	0.35 (0.48)	0.44 (0.50)	0.22 (0.41)
Asian	0.29 (0.45)	0.30 (0.46)	0.31 (0.46)	0.22 (0.41)	0.19 (0.40)	0.49 (0.50)
Hispanic	0.23 (0.42)	0.22 (0.42)	0.15 (0.35)	0.24 (0.43)	0.23 (0.42)	0.29 (0.45)
Age	20.83 (3.47)	20.90 (2.78)	21.72 (3.60)	20.16 (2.29)	21.24 (2.56)	20.35 (2.00)
#Obs.	2880	2330	610	550	620	550
#Subjects	288	233	61	55	62	55

Notes: This table reports means and standard deviations (in parentheses) for the variables used in the main analysis. For every subject, all 10 rounds with costly information acquisition are included, whereas the rounds with free information are not considered.

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 as well as another 8 consistent subjects whose information on gender, age, or ethnicity is missing.

Table C4: Determinants of Subject-Average WTP: Linear Regression

	(1)	(2)	(3)	(4)
	Full Sample	Sub-sample 1	Sub-sample 1	Sub-sample 2
IA_OwnValue	6.56*** (0.55)	6.41*** (0.56)	5.70*** (0.90)	6.11*** (1.58)
IA_OtherValue	4.51*** (0.48)	4.31*** (0.54)	4.00*** (0.91)	4.34** (1.72)
DA_OwnValue	4.44*** (0.63)	4.16*** (0.70)	3.66*** (0.87)	4.18** (1.60)
DA_OtherValue	2.21*** (0.30)	1.92*** (0.27)	2.02** (0.91)	2.80* (1.61)
Misunderstanding DA <sup>a</sup>			5.44*** (1.85)	4.87** (2.16)
Curiosity			0.29*** (0.05)	0.28*** (0.04)
Order: Costly-Free			1.61*** (0.36)	1.62*** (0.32)
Risk Aversion			-0.27** (0.11)	-0.20* (0.11)
Female				-0.73 (0.44)
Graduate Student				-0.71 (0.45)
Black				-0.81 (0.56)
Asian				-1.28* (0.63)
Hispanic				-0.67 (0.48)
<i>N</i>	288	241	241	233
<i>R</i> <sup>2</sup>	0.65	0.63	0.73	0.75

Notes: Outcome variable is subject-level average WTP for information. Columns (2)-(4) exclude participants with multiple switching points in the Holt-Laury lottery game or making inconsistent choices. Column (4) further excludes observations with missing age/gender/ethnicity information and includes other controls: age, ACT score, SAT score, dummy for ACT score missing, dummy for SAT score Missing, and dummy for degree missing. Standard errors clustered at session level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

a. "Misunderstanding DA" is defined as the percentage of times when the subject played dominated strategies (i.e., non-truth-telling) in the OwnValue or OtherValue treatment of DA in rounds without information acquisition. Mean = 0.09, standard deviation = 0.14 among all subjects ( $n = 144$ ) played the information acquisition game under DA. Only rounds without information acquisition, i.e., with no information or free information provision, are considered. This variable equals to zero for both treatment of IA, because dominant strategies are not defined under IA.

Table C5: Determinants of WTP: Fixed Effects Model and IV Regression Results

	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	IV	1st Stage
high.B $\times$ IA.OtherValue	2.39** (0.94)	2.36** (0.98)	2.39** (0.94)	2.38*** (0.88)	-0.06 (0.25)
high.B $\times$ DA.OtherValue	-0.00 (0.44)	-0.03 (0.37)	-0.01 (0.44)	-0.01 (0.38)	-0.04 (0.23)
Accumulated wealth	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Successfully acquired info in $t - 1$	0.01 (0.26)	-0.11 (0.25)	-0.03 (0.24)	-0.03 (0.22)	-0.19* (0.11)
Round	-0.14** (0.06)	-0.19** (0.08)	-0.14** (0.06)	-0.15** (0.06)	-0.08 (0.06)
Round $\times$ Free-Costly	0.09 (0.06)	0.08 (0.06)	0.09 (0.06)	0.08 (0.05)	-0.01 (0.03)
Average WTP of others in $t - 1$	-0.03 (0.02)	0.08*** (0.02)	-0.02 (0.02)	0.00 (0.03)	0.17*** (0.02)
Guess of others' WTP in $t - 1$	-0.05 (0.06)	0.12** (0.05)			0.26*** (0.03)
Guess of others' WTP in $t$	0.63*** (0.08)		0.61*** (0.08)	0.44** (0.18)	
$N$	2097	2097	2097	2097	2097
$R^2$	0.19	0.07	0.19	0.18	0.20

Notes: Outcome variable is WTP for information of each subject in each round. Regressions exclude participants with multiple switching points in the Holt-Laury lottery game or making dominated choices as well as subjects with missing age/gender/ethnicity information. Standard errors clustered at session level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

"Guess of others' WTP in  $t - 1$ " is used as IV for "Guess of others' WTP in  $t$ " (1st-stage results in the last column, i.e. outcome = "Guess of others' WTP in  $t$ ").

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  $WTP\_Guess_{i,t}$  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 0.50 (p-value 0.48), which leads us to conclude that  $WTP\_Guess_{i,t}$  is exogenous.

In summary, the results in Table C5 are similar to those in Tables 5 and 6 from a random effect Tobit model. Moreover, the IV results in Column (4) are not that different from other results in Table C5.

When we repeat the same analyses with random effect panel regressions, we obtain similar results as well (Table C6).

## C.2 Decomposition based on Pooled Regression

Table 7 in Section 5.1 presents the decomposition of excess WTP based on Tobit models for each treatment. As a robustness check, we also present results based on the pooled regression (Table C7). Although results change to some extent, we still find “conformity” explains the most part of the excess WTP.

Table C6: Determinants of WTP: Random Effects Model and IV Regression Results

	(1)	(2)	(3)	(4)	(5)
	RE	RE	RE	IV	1st Stage
IA_OwnValue	1.28*** (0.42)	2.15*** (0.42)	1.19*** (0.43)	1.42** (0.58)	0.51*** (0.19)
IA_OtherValue	0.18 (0.51)	0.58 (0.49)	0.14 (0.49)	0.25 (0.68)	0.19 (0.13)
DA_OwnValue	1.13*** (0.35)	1.13** (0.44)	1.10*** (0.35)	1.13** (0.51)	-0.18 (0.15)
high_B × IA_OtherValue	2.48*** (0.92)	2.46** (0.96)	2.48*** (0.93)	2.48*** (0.93)	-0.04 (0.21)
high_B × DA_OtherValue	0.10 (0.41)	0.07 (0.34)	0.10 (0.41)	0.10 (0.43)	-0.10 (0.18)
Accumulated wealth	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Successfully acquired info in $t - 1$	0.67*** (0.23)	0.65*** (0.22)	0.64*** (0.21)	0.66** (0.27)	-0.10 (0.08)
Round	-0.05 (0.06)	-0.07 (0.06)	-0.05 (0.06)	-0.05 (0.06)	-0.00 (0.02)
Round × Free-Costly	0.08 (0.06)	0.08 (0.06)	0.08 (0.06)	0.08 (0.05)	0.03 (0.02)
Average WTP of others in $t - 1$	-0.06*** (0.02)	0.06*** (0.02)	-0.06*** (0.02)	-0.04** (0.02)	0.19*** (0.02)
Guess of others' WTP in $t - 1$	-0.04 (0.06)	0.26*** (0.05)			0.64*** (0.04)
Guess of others' WTP in $t$	0.70*** (0.07)		0.67*** (0.06)	0.59*** (0.12)	
Misunderstanding DA	2.38 (1.70)	3.28* (1.94)	2.35 (1.69)	2.53 (1.99)	0.84 (0.62)
Curiosity	0.21*** (0.04)	0.26*** (0.04)	0.21*** (0.04)	0.22*** (0.04)	0.05*** (0.01)
Costly-Free	0.52 (0.55)	1.08* (0.61)	0.50 (0.54)	0.61 (0.63)	0.51** (0.21)
Risk Aversion	-0.21** (0.10)	-0.19** (0.10)	-0.21** (0.10)	-0.20* (0.11)	0.01 (0.03)
# of Observations	2097	2097	2097	2097	2097
# of Subjects	231	231	231	231	231

Notes: The regression sample is the same as that in Column (5) in Table 6. Each of the 231 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, and dummy for degree missing. Standard errors clustered at session level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

“Guess of others’ WTP in  $t - 1$ ” is used as IV for “Guess of others’ WTP in  $t$ ” (1st-stage results in the last column, i.e. outcome = “Guess of others’ WTP in  $t$ ”).

Table C7: Decomposition of Subject WTP for Information Based on the Pooled Regression

	IA OwnValue	IA OtherValue	DA OwnValue	DA OtherValue
WTP: data	6.49 (4.86)	4.29 (4.67)	4.30 (4.30)	1.78 (2.81)
Model prediction <sup>a</sup>	6.34 (2.71)	4.15 (2.93)	4.33 (2.65)	1.75 (1.71)
Risk aversion	-0.29 (0.25)	-0.25 (0.30)	-0.32 (0.29)	-0.25 (0.24)
Cognitive load	0.47 (0.47)	0.36 (0.43)	0.42 (0.44)	0.22 (0.29)
Learning over rounds	0.46 (0.38)	0.36 (0.35)	0.40 (0.36)	0.23 (0.25)
Curiosity	1.70 (1.67)	1.21 (1.45)	1.01 (1.37)	0.40 (0.87)
Conformity	4.27 (1.94)	2.70 (2.09)	2.49 (1.85)	1.07 (1.18)
Misunderstanding DA			0.41 (0.69)	0.20 (0.45)
Total <sup>b</sup>	5.45 (2.68)	3.49 (2.76)	3.30 (2.56)	1.34 (1.63)
Explained by other factors <sup>c</sup>	1.03 (4.00)	0.81 (3.88)	0.81 (3.17)	0.37 (2.21)
<b>Theoretical prediction<sup>d</sup></b>	[5.2, 8]	[0, 0.24]	0.67	0
# of Observations	549	495	558	495
# of Subjects	61	55	62	55

Notes: Decompositions are based on a random effects panel Tobit model that pools observations from all four treatment (Columns (5) in Table 6). 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 truncated to be in  $[0, 15]$ .

b. "Total" 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 truncation at 0 and 15.

c. "Explained by other factors" is the difference between the observed WTP and the total WTP explained by the six factors.

d. These are the theoretical predictions for risk neutral subjects.

## Appendix D Experimental Instructions: DA, Own Value

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	<input type="checkbox"/>
B	<input type="checkbox"/>
C	<input type="checkbox"/>

**Lottery:** Suppose the lottery produces the following order:

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	→ <input type="checkbox"/>	
3 →	B	→ <input type="checkbox"/>	
→	C	→ <input type="checkbox"/>	

**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	→ <input type="checkbox"/>	
→	B	→ <input type="checkbox"/>	
→	C	→ <input type="checkbox"/>	

**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	→ <input type="checkbox"/>	
→	B	→ <input type="checkbox"/>	
→	C	→ <input type="checkbox"/>	

**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	→ <input type="checkbox"/>	
→	B	→ <input type="checkbox"/>	
→	C	→ <input type="checkbox"/>	

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.,  $(\text{your guess} - \text{the actual average})^2$ . 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 E Analyses of the Game in the Experiment under with Risk-Neutral Students

Given the payoff table introduced in Section 4, this appendix derives in details the equilibrium strategies and payoffs under the assumption that every student is risk neutral. We also vary information structure and derive the incentive to acquire information. The results on risk-averse students are presented in Appendix F. Throughout, students do not know the realization of tie breakers when playing the game.

### E.1 Information Structure

We consider the following 5 scenarios where information structure differs:

- (1) Complete information on preferences: Everyone knows her own and others' realized preferences;
- (2) Incomplete information on preferences: Everyone knows her own realized preferences but only the distribution of others';
- (3) Unknown preferences: Everyone only knows the distribution of her own preferences and of others';
- (4) Unknown preferences (Scenario (3)) with acquisition of information on one's own preferences;
- (5) Incomplete information (Scenario (2)) with acquisition of information on others' preferences.

The literature on school choice, or on matching in general, focuses on the first two scenarios – complete or incomplete information. By introducing scenarios (3)-(5), we extend the literature by endogenizing the acquisition of information on one's own or on others' preferences.

Figure E1 shows the relationship among the five scenarios.

### E.2 Scenario (1): Complete Information on Preferences

**The Immediate Acceptance Mechanism** Given any realization of the preferences, we have the following symmetric equilibrium strategies and payoffs under the Immediate Acceptance mechanism (Table E8).

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:

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

**The DA Mechanism** Before looking at equilibrium, we use the following table to clarify the assignment probabilities given students' actions (Table E9). Note that we always use DA with single tie-breaking.

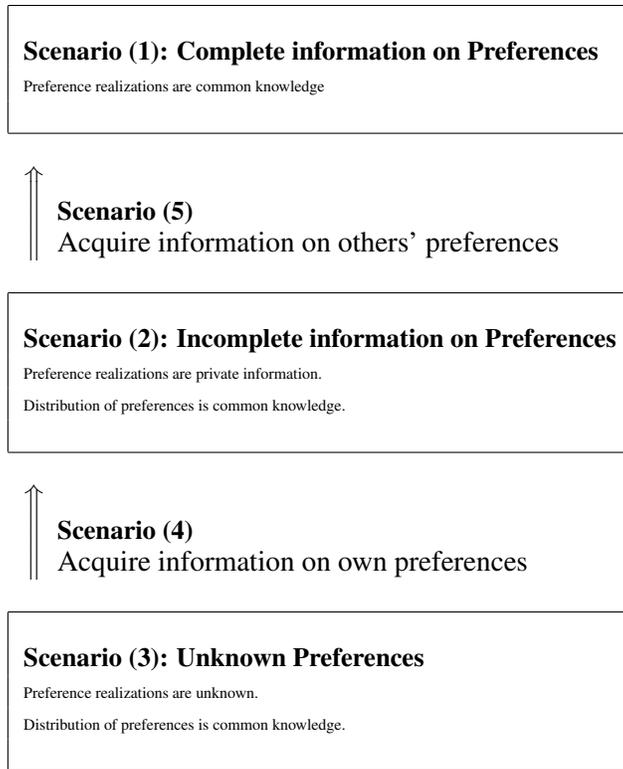


Figure E1: Scenarios Considered and the Corresponding Information Structure

Table E8: Symmetric Equilibrium under IA given Each Realization of Preference Profiles

Realization of Preference	Probability Realized	Strategy given realized type		Payoff given realized type	
		(1, 0.1, 0)	(1, 1.1, 0)	(1, 0.1, 0)	(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. As long as everyone has the same probability to play (a,b,c), the expected payoff of everyone is also 7/10.

Given any realization of the preferences, we have the following equilibrium strategies and payoffs under DA (Table E10).

Table E9: 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)	1/3	1/3	1/3	-	-	-
(a, b, c)						
(b, a, c)						
(a, b, c)	1/2	1/6	1/3	0	2/3	1/3
(a, b, c)						
(b, a, c)						
(b, a, c)	2/3	0	1/3	1/6	1/2	1/3
(a, b, c)						
(b, a, c)						
(b, a, c)	-	-	-	1/3	1/3	1/3
(b, a, c)						

Table E10: Equilibrium under DA given each Realization of Preference Profiles

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

*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:

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

### E.3 Scenario (2): Incomplete Information on Preferences

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

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

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

Types	Probability	Others' Strategy 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, 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 ex ante payoff to every student is:

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

**Remark E1.** Note that the two scenarios, (1) and (2), result in the same ex ante payoffs under IA.

**Remark E2.** In neither scenarios, a type-(1, 0.1, 0) student is ever matched with school B as long as there is at least one type-(1, 1.1, 0) student.

**The DA Mechanism** 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: For a type-(1, 0.1, 0)

	Types	Probability	Others' Strategy 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)

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 ex ante 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 E3.** Note that the two scenarios, (1) and (2), result in the same ex ante payoffs under DA.

**Remark E4.** 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.

#### E.4 Scenario (3): Unknown Preferences

**The Immediate Acceptance Mechanism** Under IA, the unique symmetric equilibrium is that everyone plays  $\sigma_{BM}^{(3)} = (a, b, c)$ . 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 an 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 E5.** In Scenario (2), the ex ante payoff is  $\frac{397}{750}$  which is higher than that of Scenario (3),  $\frac{225}{750}$ .

**Remark E6.** 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 the Immediate Acceptance.

**The DA Mechanism** 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 an 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 E7.** In Scenario (2), the ex ante payoff is  $\frac{365}{750}$  which is higher than that of Scenario (3),  $\frac{325}{750}$ .

**Remark E8.** 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 E9.** The benefit of providing free information on own preferences is higher under the Immediate Acceptance.

**Remark E10.** In Scenarios (3), the Immediate Acceptance mechanism achieves the same outcome as DA.

In the following, we discuss students' incentives to acquire information on one's own preferences.

### E.5 Scenario (4): (3) + acquisition of information on one's own preferences

**The Immediate Acceptance Mechanism** Now suppose that students only know the distribution of their own and others' preferences. We consider their incentives to acquire information on their own preferences.

After acquiring the 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 own preference.

Willingness to pay for information on own preferences can be defined in the following three cases:

- $w_0^{own}$  : when no other informed students;
- $w_1^{own}$  : when there is another informed student;
- $w_2^{own}$  : when there are two other informed students.

The following table summarizes the equilibrium strategies and *ex ante* payoffs for informed and uninformed players (Table E11).

Table E11: Willingness to Pay for Information on 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)	$\frac{397}{750}$	-	

**Overt and covert information acquisition:** 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 is purely about one's own preferences, while all other information is costless.

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

- (One) *Informed* :  $\sigma((1, 1.1, 0)) = (b, a, c)$  and  $\sigma((1, 0.1, 0)) = (a, b, c)$ ;
- (Two) *Uninformed* :  $(a, b, c)$ ,

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 willingness to pay 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:

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

Informed students obtain an ex ante payoff:

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

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:

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

This implies that the willingness to pay 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:

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

Therefore, the willingness to pay is:

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

**Remark E11.** *The willingness to pay depends on the number of informed students. When the cost is lower than  $w_2^{own}$ , all students choose to be informed.*

**Remark E12.** *When more students are informed, the incentive to acquire information is lower.*

**Remark E13.** *Information acquisition has externalities. Namely, when more students are informed, the payoffs to uninformed students are higher.*

**Remark E14.** *If we only elicit one amount of willingness to pay, an student reports a number in  $[\frac{39}{750}, \frac{60}{750}]$ , because she forms a probability distribution over the three possible realizations – playing against another 0-2 informed students.*

**The DA Mechanism** Now we consider DA. Students only know the distribution of their own and others' preferences. The following table, Table E12, summarizes the equilibrium strategies and ex ante payoffs for informed and uninformed players under DA.

Table E12: Willingness to Pay for Information on 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 an student acquires this information, the unique equilibrium in the school choice game is:

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

The informed student obtains an expected payoff:

$$\frac{1}{5} \left( \frac{112}{103} \right) + \frac{4}{5} \left( \frac{1}{3} \left( \frac{1}{10} + 1 + 0 \right) \right) = \frac{330}{750}.$$

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 willingness to pay 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:

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

Informed students obtain an ex ante payoff:

$$\frac{1}{5} \left( \frac{1}{5} \left( \frac{11}{20} + \frac{1}{6} \right) + \frac{4}{5} \left( \frac{11}{10} \cdot \frac{2}{3} \right) \right) + \frac{4}{5} \left( \frac{1}{5} \left( \frac{1}{2} + \frac{1}{60} \right) + \frac{4}{5} \left( \frac{11}{30} \right) \right) = \frac{347.5}{750}.$$

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:

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

This implies that the willingness to pay 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 willingness to pay is:

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

**Remark E15.** *The willingness to pay is independent of the number of informed students.*

**Remark E16.** *Information acquisition has very large externalities.*

**Remark E17.** *If we only elicit one amount of willingness to pay, an student reports  $\frac{5}{750}$ .*

## E.6 Scenario (5): (2) + acquisition of information on others' preferences

**The Immediate Acceptance Mechanism** Now suppose everyone knows her own preferences but not others', while the distribution of preferences is common knowledge. With some abuse of terminology, an student is informed if she knows the realization of others' preferences and whether each student is informed or uninformed. An uninformed student knows her own preferences, but neither others' preference realizations nor how many being informed is revealed to uninformed students.

Here, two pieces of information, i.e., other students' preferences and whether they are informed or not, are always acquired together, never separately. 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).

Willingness to pay for information on others' preferences can be similarly defined in the following three cases:

- $w_0^{other}$  : when no other informed students;
- $w_1^{other}$  : when there is another informed student;
- $w_2^{other}$  : when there are two other informed students.

Table E13 summarizes the equilibrium strategies and ex ante payoffs for informed and uninformed players under the Immediate Acceptance mechanism.

Table E13: Willingness to Pay for Information on Others' Payoffs under IA

# of Players		Ex Ante 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 is no other students informed, 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 on others and becomes informed, the school choice game has the following equilibrium:

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

and the informed player's strategies are summarized in Table E14:

Table E14: Equilibrium Strategies of the Player Informed of Others' Payoffs under IA

Others' Preferences	Ex Ante Probability	Strategy: Informed Player		Ex Post Payoff: Informed Player	
		(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)	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 ex ante payoff to the informed player is:

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

Therefore, conditional on being type (1, 1.1, 0), the willingness to pay 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:

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

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

When there is one other student informed, 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 on others and becomes informed, the school choice game has the following equilibrium in pure strategies:

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

and the informed player's strategy is in the following table (Table E15):

Table E15: Equilibrium Strategies with One Informed and Two Uninformed Players under IA

Others' Preferences		Ex Ante	Strategy: 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 <sup>a</sup> (b, a, c) w/ prob. 1/7 <sup>a</sup>	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 on others' preferences, which is  $[0, 9/750]$  for a type-(1,1.1,0) student, includes all these values.

The ex ante payoff to an informed player is:

$$\begin{aligned} & \frac{4}{5} \left( \frac{11}{30} \frac{16}{25} + \frac{1}{2} \frac{8}{25} + \frac{1}{25} \right) + \frac{1}{5} \left( \frac{11}{10} \frac{16}{25} + \frac{11}{20} \frac{8}{25} + \frac{4}{7} \frac{1}{25} \right) \\ &= \frac{4}{5} \frac{326}{750} + \frac{1}{5} \frac{1158}{175} \\ &= \frac{396.22857}{750}. \end{aligned}$$

Therefore, conditional on being type (1, 1.1, 0), the willingness to pay given there is another informed agent is:

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

When there are two other agents 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 being informed. When two other agents are informed, the third agent, if being uninformed, 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 incentive to acquire information.

**Remark E18.** *When only one amount of willingness to pay is elicited, a type-(1, 1.1, 0) student*

reports a number in  $[0, \frac{9}{750}]$ . Averaging over all student *ex ante*, the WTP for information on others's preferences is in  $[0, \frac{1.8}{750}]$ .

**The DA Mechanism** Since reporting truthfully is a dominant strategy, there is no incentive to know others' preferences.

## Appendix F Analyses of the Game in the Experiment with Risk-Averse Students

This appendix compares risk-neutral and risk-averse students in terms of their willingness to pay for information.

Risk-neutral students have the same cardinal preferences as before (Table 1), and risk-averse students have their von Neumann–Morgenstern utilities associated with each schools as in Table F16.

Table F16: Preference/Payoff Table for Risk-Averse Students

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

Note that  $\sqrt{0.1} \approx 0.316$ , and  $\sqrt{1.1} \approx 1.049$ . 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.<sup>16</sup>

**Conclusion F1.** *WTP for own values is smaller for risk-averse students; WTP for others' values is similar when measured as the percentage of expected utilities, but it is much lower when measured in dollars.*

### F.1 Information on Own Values

Willingness to pay can be measured in dollars. However, one dollar does not mean the same in the two cases. Therefore, it is also measured as a percentage of the expected utility under complete information and then of the one under no information.

Table F17: WTP for Info on Own Values: Risk-Averse and 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	0.077	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.

<sup>16</sup>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.

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

Table F18: Willingness to Pay for Info on Own Values: Risk-Averse and Risk-Neutral Students under the 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.

## F.2 Information on Others' Values

Note that the willingness to pay 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 F19: WTP for Info on Others' Values: Risk-Averse and 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.