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**TOWARD AN UNDERSTANDING  
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Shigehiro Serizawa  
Natsumi Shimada  
Tiffany Tsz Kwan Tse

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The Institute of Social and Economic Research  
The University of Osaka  
6-1 Mihogaoka, Ibaraki, Osaka 567-0047, Japan

# Toward an Understanding of Dominated Bidding in a Vickrey Auction Experiment\*

Shigehiro Serizawa<sup>†</sup> Natsumi Shimada<sup>‡</sup>. Tiffany Tsz Kwan Tse<sup>§</sup>

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## Abstract

This study explores two key factors influencing subjects' deviation from dominant bidding in Vickrey auction experiments. The first factor examines subjects' understanding of strategy-proofness (SP), while the second focuses on "human interaction" which includes social preferences (spite and altruism), responses to strategic uncertainty, and tacit collusion. To analyze the effect of understanding SP, we quiz subjects before an experimental Vickrey auction and examine whether their bidding behavior changes if one of the quizzes includes hints about SP. We design the quiz carefully, incorporating implicit hints about SP and ensuring the avoidance of explicit demands or advice to mitigate experimenter demand effects. However, completing the quiz enables the subjects to understand SP themselves. To analyze the effects of human interaction, we examine whether subjects' bidding behavior changes if they compete against robots instead of human rivals in the auctions. We design  $2 \times 2$  treatments by varying the type of quiz (with or without hints about SP) and the nature of the rivals (humans or robots). We found that the quiz with hints about SP increases dominant bidding. While the nature of rivals also influences bidding behavior among subjects with a higher understanding of SP, its effect is less robust than that of the SP hints. Thus, the main factor causing dominated bidding in Vickrey auction experiments is not human interaction but a lack of understanding of SP.

**Keywords:** Market design; Strategy-proofness; Vickrey auction; Hints; Human interaction; Human vs. robot rivals

**JEL Classification:** D44, D82, D61

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<sup>†</sup> Faculty of Economics, Osaka University of Economics, Japan. E-mail: serizawa.8558@gmail.com

<sup>‡</sup> Graduate School of Economics and Management, Tohoku University, Japan. E-mail: 18n.shimada@gmail.com

<sup>§</sup> Corresponding author: Institute of Social and Economic Research, University of Osaka, Japan. E-mail: tiffany.econ@gmail.com

# 1 Introduction

The Vickrey auction (Vickrey, 1961) is strategy-proof (SP). It is a dominant strategy for each bidder to bid according to her true valuation, which we call *dominant* bidding. However, many experimental studies have reported that most subjects deviate from dominant bidding in Vickrey auctions with single units (Garratt et al., 2012; Kagel and Levin, 1993; Shogren et al., 2006) and multiple units (Kagel and Levin, 2009; Manelli et al., 2006; Masuda et al., 2022). We call such deviation *dominated* bidding.

In experiments, many researchers have proposed hypotheses to explain dominated bidding, such as the joy of winning (Cooper and Fang, 2008), spiteful behaviors (Andreoni et al., 2007; Nishimura et al., 2011), underestimation of possible losses (Georganas et al., 2017), cognitive limit of reasoning (Li, 2017; Pycia and Troyan, 2023) and strategic complexity (Nagel and Saitto, 2023). These studies suggest that several factors may cause dominated bidding in Vickrey auctions.

Vickrey auctions are SP but complex (Li, 2017; Pycia and Troyan, 2023; Nagel and Saitto, 2023). Subjects' cognitive reasoning limitations may make it difficult for them to understand the property of SP in Vickrey auction rules. Conversely, most subjects find it easier to understand that bidding one's true valuation is a dominant strategy in ascending auctions. Li (2017) proposed a stronger version of SP, called *obvious strategy-proofness*. Under this framework, Vickrey auctions are SP but not obviously SP, whereas ascending auctions are both SP and obviously SP. Li (2017) demonstrated that this distinction helps explain the divergent performance observed between Vickrey and ascending auctions, despite both being SP in theory. In matching models, Hassidim et al. (2017) proposed a potential explanation for preference misrepresentation—subjects in the experiments may have failed to understand the SP nature of the deferred acceptance mechanism, a widely recognized SP mechanism.

Several researchers guide subjects to address the difficulty of understanding SP by providing advice. They examine whether this advice contributes to an increase in truth-telling rates across various SP mechanisms, such as pivotal mechanism (Kawagoe and Mori, 2001), top trading cycle matching algorithms (Guillen and Hing, 2014; Guillen and Hakimov, 2018), school matching mechanisms (Ding and Schotter, 2019), and multi-

unit Vickrey auctions (Masuda et al., 2022). Masuda et al. (2022) found that providing advice guiding subjects to bid their true value increased the rate of dominant bidding from 20% to 47%. However, it remains unclear whether subjects express their genuine preferences because they understand SP or if they simply follow the guidance as a result of experimenter demand effects (Zizzo, 2010). In contrast, we analyze the effect of understanding SP while minimizing experimenter demand effects.

To promote subjects' understanding of SP without inducing demand effects, we administer quizzes containing hints about SP. These quizzes refrain from offering explicit advice; however, completing them enables subjects to understand the property of SP independently. In essence, by solving the quizzes, subjects come to realize that the Vickrey auction is strategy-proof. Thus, the effect of these quizzes on subjects' bidding behavior can be attributed to the factor of understanding SP.

Specifically, we designed three distinct types of quizzes: **Basic Quiz**, **Advanced Quiz with hints about strategy-proofness** (hereafter, *Hint Advanced Quiz*), and **Advanced Quiz without hints about strategy-proofness** (hereafter, *No-Hint Advanced Quiz*). All subjects complete these quizzes before the auction begins. The Basic Quiz assesses whether subjects comprehend the auction rules and, at the same time, reinforces their comprehension of the rules. It is administered to all subjects immediately after they receive the initial instructions. The Hint Advanced Quiz assesses whether subjects understand the property of SP and, at the same time, enhances their understanding of it. This quiz is administered, immediately after the Basic Quiz, to subjects in two of the four treatments. The No-Hint Advanced Quiz closely mirrors the Hint Advanced Quiz but avoids SP hints. It focuses solely on payoff calculations in the Vickrey auction. Its purpose is to equalize subjects' earnings and their comprehension levels of the auction rules, without exposing them to hints about strategy-proofness prior to the auction. This quiz is administered, immediately after the Basic Quiz, to subjects in the remaining two treatments. Our analysis of subjects' understanding of SP compares the effects of the Hint Advanced Quiz and the No-Hint Advanced Quiz on their bidding behavior.

As noted earlier, dominated bidding in Vickrey auctions may be driven by multiple

factors. In addition to examining the effect of understanding SP, we investigate another important factor, which we refer to as “human interaction.” This factor encompasses several elements, including social preferences (such as spite and altruism), responses to strategic uncertainty about other bidders’ behavior, and tacit collusion. All of these forces arise from interactions among human subjects.

These human-interaction factors do not influence bidding behavior when each subject competes exclusively against robot rivals whose bids are automatically generated from a known distribution. In this controlled environment, the effect of understanding SP on bidding behavior can be observed in a purer form. Accordingly, in two of the four treatments, we conduct an auction experiment in which each human subject competes against robot rivals to isolate the effect of understanding SP. At the same time, we identify the impact of human interaction by contrasting the bidding behavior in the two treatments, where each subject competes against robot rivals, with those in the other two treatments, where only human subjects compete.

Several recent studies employ experimental designs in which human subjects compete against robot bidders in auction settings (Chen and Takeuchi, 2010; Kagel and Levin, 2001, 2009).<sup>5</sup> These studies typically examine how subjects learn about the robots’ bidding strategies and how they respond to them. In contrast, our objective is to minimize such learning and strategic-response effects, so that the impacts of understanding SP and human interaction can be observed in purer forms. To this end, we inform subjects that the robot bidders’ bids are automatically generated from a known distribution. We deliberately avoid mentioning the robots’ strategies or even their valuations, in order to prevent subjects from consciously reasoning about or attempting to infer the robots’ strategic behavior.

In summary, our study focuses on two factors that may influence the rate of dominant bidding in Vickrey auctions: understanding SP and human interaction. To identify the effects of these two factors, we implement a  $2 \times 2$  experimental design that varies (i) whether subjects complete the Hint Advanced Quiz or the Advanced Quiz without hints, and (ii) whether they compete against human rivals or robot rivals. It is worth

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<sup>5</sup> In addition to auction experiments, the interactions between human subjects and robots have been investigated in public goods game experiments (Yamakawa et al., 2016).

emphasizing that our paper differs from the existing literature mentioned above in that we analyze both factors—understanding SP and human interaction—within a unified framework and directly compare their relative magnitudes.

In our experiment, we auction two homogeneous units. There are two reasons for choosing a multi-unit Vickrey auction. First, the multi-unit Vickrey auction is more complex than a single-unit Vickrey (second-price) auction. As a result, understanding the property of SP is more challenging for subjects in the multi-unit setting. Indeed, extremely low rates of dominant bidding—around 20%—have been reported in multi-unit Vickrey auction experiments, such as Kagel and Levin (2009) and Masuda et al. (2022). In this environment, the effects of understanding SP and human interaction are likely to be more pronounced and therefore easier to detect. To generate a wider variation in subjects’ levels of understanding of SP, we therefore adopt a multi-unit Vickrey auction rather than a single-unit auction. Second, multi-unit auctions are widely used in practice, for example in spectrum auctions and treasury bill auctions, even though Vickrey-type formats themselves are not commonly implemented.

In our experimental results, most subjects obtain the maximum or near-maximum score on the Basic Quiz. This indicates that they have a solid comprehension of the Vickrey auction rules. Hence, it is unlikely that dominated bidding can be attributed to a lack of comprehension of the auction rules. Moreover, even in the treatments where human interaction is eliminated—namely, when each subject competes against robot rivals—dominated bidding persists. This finding suggests that human interaction can explain only part of the occurrence of dominated bids in Vickrey auctions.

We find that providing hints about SP (the Hint Advanced Quiz) increases the frequency of dominant bidding in the Vickrey auction. This effect holds regardless of whether subjects compete against human or robot rivals. In addition, subjects who achieve higher scores on the Hint Advanced Quiz tend to submit dominant bids more frequently. These results indicate that a better understanding of SP leads subjects to bid their true valuations more often. Overall, the evidence suggests that the primary cause of dominated bidding in Vickrey auctions is subjects’ difficulty in understanding SP, while the effect of human interaction, though present, appears to be smaller.

Auction outcomes are highly efficient, with efficiency rates of approximately 98% across all treatments. However, bidders' payoffs and the seller's total revenue exhibit mixed patterns across treatments. The overall effect size of the Hint Advanced Quiz is comparable to that of the advice studied by Masuda et al. (2022). Notably, however, such advice increases dominant bidding mainly among subjects with a lower initial understanding of SP, but has little effect on those with a higher level of understanding.

The remainder of this paper is organized as follows. Section 2 describes the experimental design and presents several proposed hypotheses. Subsequently, Section 3 presents our experimental results, and Section 4 discusses efficiency, the bidder's payoff, and the seller's total revenue. Section 5 presents a comparison of the effect size of advice and the Hint Advanced Quiz. Finally, Section 6 concludes the paper.

## 2 Experimental Design

The purpose of this experiment is to investigate two factors that influence the dominant bid rates in a multi-unit Vickrey auction: (i) the understanding of SP and (ii) human interaction. Our experimental design follows that of Masuda et al. (2022). For the theoretical background of the multi-unit Vickrey auction, please refer to Masuda et al. (2022).

### 2.1 Theoretical considerations

There are three bidders,  $\{1, 2, 3\}$ , and two indivisible, identical objects to be auctioned. Each bidder is allowed to bid for two units. Bidder  $i$ 's *valuation* of objects is  $v_i = (v_i^1, v_i^2)$ , where  $v_i^1 \geq v_i^2 \geq 0$  and  $v_i^j$  denote the valuations that bidder  $i$  assigns to the  $j$ -th unit. Given any  $v_i$ , bidder  $i$ 's utility of obtaining  $k$  units of objects and paying  $m_i$  units of money is as follows:<sup>6</sup>

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<sup>6</sup> In standard auctions, such as the Vickrey auction,  $m_i = 0$  if  $k = 0$ .

$$U(k, m_i; v_i) \equiv \begin{cases} v_i^1 + v_i^2 - m_i & \text{if } k = 2 \\ v_i^1 - m_i & \text{if } k = 1 \\ -m_i & \text{if } k = 0. \end{cases}$$

A list  $v = (v_1, v_2, v_3)$  is a *valuation profile*. The *bid* submitted by bidder  $i$  is denoted as  $b_i = (b_i^1, b_i^2)$ , where  $b_i^1 \geq b_i^2 \geq 0$  and  $b_i^j$  denote the bidder  $i$ 's bid for the  $j$ -th unit. Let  $b = (b_1, b_2, b_3)$  be the *bid profile*.

An *assignment function* is a function  $d = (d_1, d_2, d_3)$  that specifies, for each bid profile  $b$  and each bidder  $i$ , the number  $d_i(b) \in \{0, 1, 2\}$  of the objects bidder  $i$  obtains. The resource constraint requires that for each bid profile  $b$ ,  $d_1(b) + d_2(b) + d_3(b) = 2$ . A *payment function* is a function  $m = (m_1, m_2, m_3)$  that specifies, for each bid profile  $b$  and each bidder  $i$ , the payment  $m_i(b)$  made by bidder  $i$ . A *rule* is a pair of assignment and payment functions  $(d, m)$ .

We focus on rules under which bidding true valuations is a weakly dominant strategy for each bidder. Formally,

**Strategy-proofness (SP):** For each bidder  $i$ , each bidder  $i$ 's valuation  $v_i$ , each bidder  $i$ 's bid  $b_i$ , and all other bids  $b_{-i}$ ,

$$U(d_i(v_i, b_{-i}), m_i(v_i, b_{-i}); v_i) \geq U(d_i(b_i, b_{-i}), m_i(b_i, b_{-i}); v_i).$$

Vickrey auction rules are central to the auction theory literature.

**Vickrey auction:** Each bidder  $i$  simultaneously submits her bid  $b_i = (b_i^1, b_i^2)$ . After observing the bid profile, the seller ranks the six bids  $\{b_i^k : i = 1, 2, 3 \text{ \& } k = 1, 2\}$  from highest to lowest and allocates the two units to the two highest bids. Ties are broken by equal probabilities. If a bidder wins one (or two) unit, the payment is the highest bid (the sum of the two highest bids) among the losing bids submitted by the other bidders. If a bidder wins no units, the payment is zero.

The most important feature of the Vickrey auction is that it is strategy-proof. How-

ever, several experimental studies report that bidders tend to overbid in Vickrey auctions, that is, they submit weakly dominated bids.

## 2.2 Procedure

In each treatment, three bidders compete for two identical units. For each subject acting as a bidder, two integer valuations are independently drawn from a uniform distribution over the integers from 10 to 1,000 in increments of 10. The larger (smaller) integer is assigned as the subject’s valuation for the first (second) unit. All values are denominated in Japanese yen (JPY).

We designed four treatments that vary along two dimensions: the type of Advanced Quiz (with or without SP hints) and the nature of the rivals (human or robot). Using a between-subject design, the four treatments are as follows:

- Treatment HH-No-Hint: only human subjects compete, and each subject completes No-Hint Advanced Quiz
- Treatment HH-Hint: only human subjects compete, and each subject completes Hint Advanced Quiz
- Treatment HR-No-Hint: each subject competes with two robot rivals and completes No-Hint Advanced Quiz
- Treatment HR-Hint: each subject competes with two robot rivals and completes Hint Advanced Quiz

Table 1 summarizes the basic data for the four treatments.

The experiments were conducted at University of Osaka in eight sessions between January and March 2022. We recruited 184 students at University of Osaka registered in the ORSEE (Greiner, 2015) database of the Institute of Social and Economic Research. Each subject took part in a single session. Subjects provided their consent

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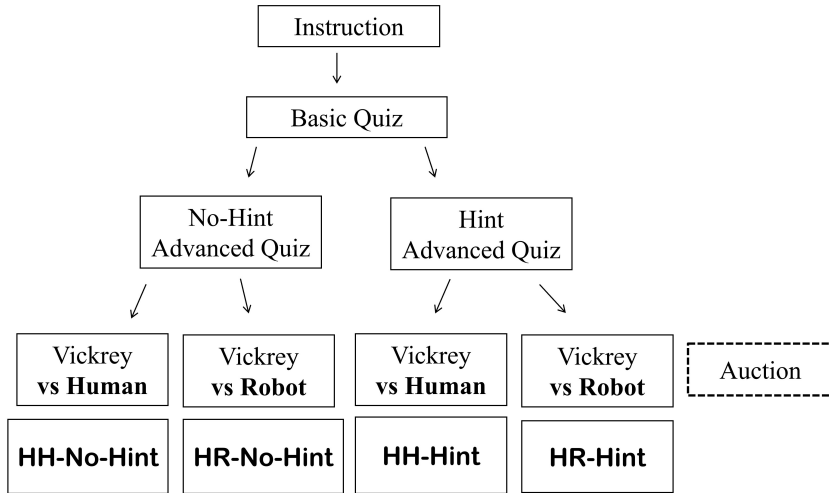
<sup>7</sup> We compare payment across treatments using an OLS regression model, regressing payment on four treatment dummies while incorporating robust standard errors. Subsequently, we compare the estimated dummy coefficients using an F test, with the results presented through Bonferroni-adjusted p-values. There is no statistically significant difference in payments across treatments ( $p = 0.604$ ).

Table 1: Summary of treatments

Treatments	HH-No-Hint	HH-Hint	HR-No-Hint	HR-Hint
Type of Advanced Quiz	w/o hints	w/ hints	w/o hints	w/ hints
Nature of rivals	human	human	robot	robot
No. of sessions	2	2	2	2
Duration (min)	150	150	150	150
No. of rounds	20	20	20	20
No. of subjects	48	45	43	48
Avg. payment (JPY) <sup>7</sup>	4,780	4,941	5,020	5,026
Avg. score of Basic Quiz	9.604	9.800	9.488	9.521
Avg. score of Hint Advanced Quiz	/	9.200	/	9.146
Avg. score of No-Hint Advanced Quiz	9.500	/	9.628	/
No. of subjects with perfect scores in the Advanced Quiz	41	31	40	37

online by clicking a button before registering for the experiment. Each session lasted approximately 150 min and was conducted by the same experimenter. Our experiment was computerized using the experimental software z-Tree (Fischbacher, 2007). Figure 1 illustrates the experimental flow.

Figure 1: Flow of the experiment



Subjects were randomly assigned to seats. Each subject received printed instructions and listened to an audio recording of the instructions. They were then given three minutes to read the instructions carefully. Throughout the experiment, subjects were not allowed to ask questions. However, they were permitted to use a calculator.

First, subjects participated in the Basic Quiz, the details of which are provided in

Subsection 2.3.1. Immediately after receiving a Basic Quiz sheet, each subject began answering the questions. Subjects earned 100 JPY for each correct answer. The quiz consisted of ten questions, with a maximum possible payoff of 1,000 JPY. The time limit for the Basic Quiz was ten minutes. After completing the Basic Quiz, subjects received the answer key and listened to an audio explanation. They were then given three minutes to review the answer key.

Second, subjects participated in the Advanced Quizzes (No-Hint Advanced Quiz and Hint Advanced Quiz), the details of which are provided in Subsections 2.3.2 and 2.3.3. In HH-No-Hint and HR-No-Hint, subjects completed the No-Hint Advanced Quiz. In HH-Hint and HR-Hint, subjects completed Hint Advanced Quiz. In both versions of the Advanced Quiz (No-Hint Advanced Quiz and Hint Advanced Quiz), subjects earned 100 JPY for each correct answer. The quiz consisted of ten questions, with a maximum possible payoff of 1,000 JPY. Subjects began answering the questions immediately, and the time limit was twenty minutes. After completing the Advanced Quiz, subjects in HH-No-Hint and HR-No-Hint received the answer key for the No-Hint Advanced Quiz, whereas those in HH-Hint and HR-Hint received the answer key for the Hint Advanced Quiz. They then listened to audio explanations and were given five minutes to review the answer keys.

Third, subjects participated in a Vickrey auction experiment. In HH-No-Hint and HH-Hint, the subjects competed against human rivals. In HR-No-Hint and HR-Hint, each human subject competed against robot rivals. The auction consisted of two practice rounds followed by 20 paid rounds under a random matching protocol. At the beginning of each round, subjects in HH-No-Hint and HH-Hint were randomly matched into groups of three with two other human subjects, and each subject in HR-No-Hint and HR-Hint was matched with two robot rivals to form a group of three. In each round, every subject received two integer valuations for two identical units. Subjects were instructed to submit two bids, each an integer between 0 and 2,000 in increments of 10. A key requirement was that the bid for the first unit had to be weakly greater than the bid for the second unit. In HR-No-Hint and HR-Hint, subjects were informed that, for each robot rival, two bids were independently drawn from a uniform distribution over

$\{10, 20, \dots, 1000\}$ ; the higher (lower) value corresponded to the first-unit (second-unit) bid.

After the 20 paid rounds, subjects completed a questionnaire and were immediately paid in cash. Each subject received a private payment equal to the sum of their earnings from the 20 auction rounds as well as their earnings from the Basic Quiz and the Advanced Quiz. The average payment was 4,780 JPY in HH-No-Hint, 4,941 JPY in HH-Hint, 5,020 JPY in HR-No-Hint, and 5,026 JPY in HR-Hint.

### 2.3 Design of Quizzes

Before the auction experiment, we administered three types of quizzes to subjects: **Basic Quiz** for all the subjects, *Hint Advanced Quiz* for subjects in HH-Hint and HR-Hint, and *No-Hint Advanced Quiz* for subjects in HH-No-Hint and HR-No-Hint. The Basic Quiz was designed to assess and reinforce subjects' comprehension of the Vickrey auction rules. The Hint Advanced Quiz assessed and reinforced subjects' understanding of SP in the Vickrey auction. The No-Hint Advanced Quiz was intended to equalize earnings opportunities and auction-rule comprehension for subjects in HH-No-Hint and HR-No-Hint making them comparable to those in HH-Hint and HR-Hint prior to the auction.

#### 2.3.1 Basic Quiz

The Basic Quiz was administered to subjects in all treatments to assess and reinforce their comprehension of the Vickrey auction rules. The quiz consisted of ten questions, with a maximum score of 10 points. Subjects received 100 JPY for each correct answer. Figure 2 presents sample questions from the Basic Quiz. As illustrated in the figure, the quiz provides numerical examples of bid profiles and valuations, and the questions ask about the corresponding winning bids, payments, and payoffs. Of the ten questions, three concern winning bids, four concern payments, and the remaining three concern payoffs.

Two of the questions involve positive payoffs, and one involves a negative payoff. Thus, if a subject answers these questions correctly, they can recognize that their payoff



Figure 3: Hint Advanced Quiz

Assume that you are bidder B, and your valuations of the first and second units are 700 and 400, respectively. Maintain these assumptions for Questions 1–10 below. For each question, select the correct answers from the choices provided in the table below, where the the first and second figures in each choice are the bids of the first and second units, respectively. If several choices are correct, select all of them.

Choice a: (900, 820)	Choice b: (780, 500)	Choice c: (700, 400)
Choice d: (400, 390)	Choice e: (310, 200)	Choice f: (660, 200)

The calculation sheets for these questions are attached on pages 4–6. Use them if necessary. (However, the calculation sheets will not be marked.)

In Questions 1 and 2, assume that you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the two questions is shown on page 4.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	380	300
C	300	250

[Question 1] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 2] Select the choices that maximize your earnings (the sum of valuations of the units you win – your payments). (Note that if the earnings from all choices are nonpositive, the maximized earnings may be zero.)

Answer: \_\_\_\_\_

In Questions 3–5, assume that you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 5.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	650	300
C	750	450

⋮

[Question 5] Select the choices that maximize your earnings (the sum of valuations of the units you win – your payments). (Note that if the earnings from all choices are nonpositive, the maximized earnings may be zero.)

Answer: \_\_\_\_\_

[Question 6] Select the choices that are the correct answers of both Questions 2 and 5—the choices that maximize your earnings for both of the two expectations about the bids of the two other bidders. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

options and is multiple-choice in nature. Five questions ask which choices yield positive, zero, or negative earnings for Bidder B given the bid profiles of the other bidders (A and C). The remaining five questions ask which choices maximize Bidder B's payoff. Because the payoff-maximizing choices are typically not unique, multiple answers may be correct. However, since the Vickrey auction is strategy-proof, Choice c (i.e., bidding one's valuations) is always among the payoff-maximizing options. Moreover, Question 10 considers three different bid profiles of the other bidders and asks which choice maximizes the payoff in all cases; in this question, Choice C is the unique correct answer.

Thus, if subjects answer the questions correctly, they may recognize that bidding one's valuations maximizes payoff regardless of the other bidders' bids, illustrating the property of strategy-proofness. Accordingly, the quiz provides implicit hints about strategy-proofness. Nevertheless, we deliberately refrained from explicitly instructing or advising subjects to bid their valuations in order to mitigate, or at least minimize, potential demand effects (Zizzo, 2009).

Calculation sheets were provided to help subjects compute payoffs efficiently. The time limit for the Hint Advanced Quiz was twenty minutes. After completing the quiz, subjects received a handout containing the correct answers and listened to an audio explanation delivered via reading software. They were then given five minutes to review the handout before the auction began.

### **2.3.3 No-Hint Advanced Quiz**

The No-Hint Advanced Quiz was administered to subjects in HH-No-Hint and HR-No-Hint. Its purpose was to equalize earnings opportunities and comprehension of the auction rules with those of subjects in HH-Hint and HR-Hint, while not enhancing their understanding of SP prior to the auction. Although the primary purpose of the Hint Advanced Quiz was to provide hints about strategy-proofness, it inevitably generates additional effects.

First, in the Hint Advanced Quiz, each correct answer earned subjects in HH-Hint and HR-Hint 100 JPY, resulting in substantial earnings from the quiz. Therefore, if subjects in HH-No-Hint and HR-No-Hint were not provided with comparable earning

Figure 4: No-Hint Advanced Quiz

Assume that you are Bidder B in Questions 1–10. For each question, select the correct answers from the choices given in the table below, where the first and second figures in each choice are the bids of the first and second units, respectively. If several choices are correct, select all of them.

Choice a: (900, 820)	Choice b: (780, 500)	Choice c: (700, 400)
Choice d: (400, 390)	Choice e: (310, 200)	Choice f: (660, 200)

The calculation sheets for these questions are attached on pages 4–6. Use them if necessary. (However, the calculation sheets are not marked.)

In Questions 1–3, assume that your valuations of the first and second units are 500 and 300, respectively, and you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 4.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	380	300
C	300	250

[Question 1] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 2] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) negative. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 3] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) positive. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

In Questions 4–6, assume that your valuations of the first and second units are 710 and 290, respectively, and you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 5.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	650	300
C	750	450

[Question 4] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 5] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) negative. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

opportunities, they might behave differently, irrespective of their understanding of SP.

However, simply granting subjects in HH-No-Hint and HR-No-Hint payments comparable to those earned by subjects in HH-Hint and HR-Hint may induce a “house money effect” (Corgnet et al., 2015). To avoid this concern, it is important to provide subjects with the opportunity to earn comparable amounts through similar effort, rather than directly transferring equivalent payments.

Second, the Hint Advanced Quiz may enhance not only subjects’ understanding of SP but also their comprehension of the auction rules. Therefore, to isolate the effect of understanding SP, it is crucial to equalize the level of auction-rule comprehension between subjects in HH-No-Hint and HR-No-Hint, and those in HH-Hint and HR-Hint.

To summarize, the purposes of No-Hint Advanced Quiz are as follows: (i) to provide subjects in HH-No-Hint and HR-No-Hint with the opportunity to earn amounts comparable to those available in the Hint Advanced Quiz through similar effort, and (ii) to equalize their earnings and comprehension of the auction rules with those of subjects in HH-Hint and HR-Hint prior to the auction. However, the No-Hint Advanced Quiz should not provide hints about strategy-proofness. We therefore constructed it as follows.

Figure 4 presents sample questions from the No-Hint Advanced Quiz. As in the Hint Advanced Quiz, the No-Hint Advanced Quiz consisted of ten questions, with a maximum score of 10 points, and subjects received 100 JPY for each correct answer. Each subject played the role of Bidder B. At the beginning of the quiz, six bidding options (Choices a–f) for the first and second units were provided, and each question required subjects to select the correct answer from these six options. Calculation sheets were also provided to help subjects compute payoffs efficiently.

However, unlike the Hint Advanced Quiz, the six bidding options in the No-Hint Advanced Quiz did not include Bidder B’s valuations. Moreover, all questions focused exclusively on whether particular bidding choices yielded positive, zero, or negative payoffs; none asked which choices maximized Bidder B’s payoff. Thus, the quiz did not provide hints about strategy-proofness. Nevertheless, it further reinforced subjects’ comprehension of the auction rules. In particular, three questions concerned bidding choices that resulted in negative payoffs. By answering these questions, subjects could

recognize that overbidding may lead to negative payoffs. In addition, Bidder B's valuations were varied across questions so that the difficulty of the No-Hint Advanced Quiz was comparable to that of the Hint Advanced Quiz. Otherwise, the No-Hint Advanced Quiz would have been substantially easier.

As reported in Subsection 3.2, the No-Hint and Hint Advanced Quizzes yielded comparable average scores. This indicates that, as intended, the difficulty level of the No-Hint Advanced Quiz was similar to that of the Hint Advanced Quiz. It also suggests that subjects' comprehension of the auction rules in HH-No-Hint and HR-No-Hint was comparable to that in HH-Hint and HR-Hint, and that subjects in HH-No-Hint and HR-No-Hint could earn amounts similar to those earned by subjects in HH-Hint and HR-Hint.

## 2.4 Hypotheses

Although the literature has firmly established the SP nature of the Vickrey auction, various experimental results have shown that many subjects overbid or underbid relative to their valuations. We hypothesize that this discrepancy may be due to the complexity of understanding the concept of SP as opposed to merely comprehending the Vickrey auction rules. To examine this, we first ensure that most of the subjects comprehend the Vickrey auction rules by administering a quiz on the rules (Basic Quiz) to all subjects. Subsequently, we administer two different types of a second quiz: one includes hints about SP (Hint Advanced Quiz) and is given to subjects in HH-Hint and HR-Hint, whereas the other lacks these hints (Advanced Quiz w/o hint) and is given to subjects in HH-No-Hint and HR-No-Hint. We predict that the Hint Advanced Quiz make subjects more aware of the benefits of dominant bidding, which leads them to bid their true values and reduces the deviation of their bids from those values. To statistically evaluate the effect of the hints about SP, we propose the following null hypothesis:

### **Hypothesis 1** (*Effect of Hints on Strategy-Proofness*)

- (a) The rate of dominant bidding among subjects who take Hint Advanced Quiz in HH-Hint is statistically similar to that among those who take No-Hint Advanced Quiz in HH-No-Hint.
- (b) The degree of deviation from the true value is also similar between subjects who

take the Hint Advanced Quiz in HH-Hint and those who take the No-Hint Advanced Quiz in HH-No-Hint.

Some experimental results suggest that other factors, such as strategic interaction and social preferences, may also play a significant role in dominated bidding. These factors are closely related to interactions among human subjects. When each subject competes against robot rivals in an auction, the human interaction factor is eliminated. Nevertheless, we predict that hints regarding SP in Advanced Quiz make the subjects more aware of the advantages of dominant bidding, even when their rivals are robots. To statistically evaluate the effect of hints about SP, we propose the following null hypothesis:

**Hypothesis 2** (*Effect of Hints on Strategy-Proofness with robot rivals*)

- (a) The rate of dominant bidding among subjects who take Hint Advanced Quiz in HR-Hint is statistically similar to that among those who take No-Hint Advanced Quiz in HR-No-Hint.
- (b) The degree of deviation from the true value among subjects who take Hint Advanced Quiz in HR-Hint is statistically similar to that among those who take No-Hint Advanced Quiz in HR-No-Hint.

To investigate the impact of factors related to human interaction, we compare the rate of dominant bidding in treatments in which each subject competes against robot rivals with the rate in treatments in which only human subjects compete. To examine the effect of human interactions on dominant bidding, we propose the following null hypotheses:

**Hypothesis 3** (*Effect of human interaction with No-Hint Advanced Quiz*)

- (a) The dominant bidding rate is similar regardless of whether subjects compete against human subjects in HH-No-Hint or solely against robot rivals in HR-No-Hint.
- (b) The degree of deviation from the true value is similar regardless of whether subjects compete against human subjects in HH-No-Hint or solely against robot rivals in HR-No-Hint.

**Hypothesis 4** (*Effect of human interaction with Hint Advanced Quiz*)

- (a) The dominant bidding rate is similar regardless of whether subjects compete against human subjects in HH-Hint or solely against robot rivals in HR-Hint.
- (b) The degree of deviation from the true value is similar regardless of whether subjects compete against human subjects in HH-Hint or solely against robot rivals in HR-Hint.

### 3 Experimental results

#### 3.1 Level of comprehension of the Vickrey auction rules.

Figure 5: Distribution of Basic Quiz scores

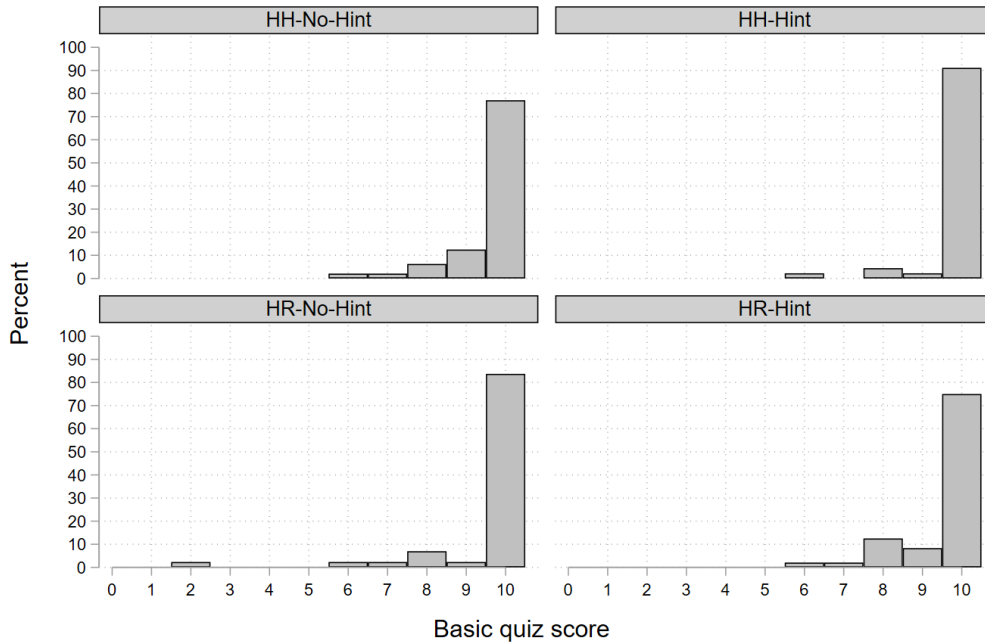


Figure 5 illustrates Basic Quiz score distributions across the four treatments. As shown, a significant majority of subjects in each treatment achieved perfect scores (77% for HH-No-Hint, 91% for HH-Hint, 84% for HR-No-Hint, and 75% for HR-Hint). Other subjects in each treatment group attained nearly perfect scores (8 or 9 points). To compare Basic Quiz scores across treatments, we employ an OLS regression model, regressing Basic Quiz scores on four treatment dummies. Robust standard errors are utilized, and the estimated dummy coefficients are compared using an F test, with results

assessed through Bonferroni-adjusted p-values. There is no statistical difference in the Basic Quiz scores across the treatments ( $p = 0.328$ ).<sup>8</sup> Most subjects in all treatments have a good comprehension of the Vickrey auction rules. Moreover, their comprehension levels do not differ across treatments.

After Basic Quiz, the correct answers are distributed to each subject and explained using voice software. As this step further enhances the comprehension, most subjects exhibit a thorough comprehension of the Vickrey auction rules prior to the auction. This is confirmed by the post-experiment survey (See Online Appendix): 79.167% of HH-No-Hint subjects, 91.111% of HH-Hint subjects, 74.419% of HR-No-Hint subjects, and 75% of HR-Hint subjects indicated that they understood the Vickrey auction rules thoroughly before the auction commenced.

### 3.2 Level of understanding of the strategy-proofness

Figure 6: Distribution of Advanced Quiz scores

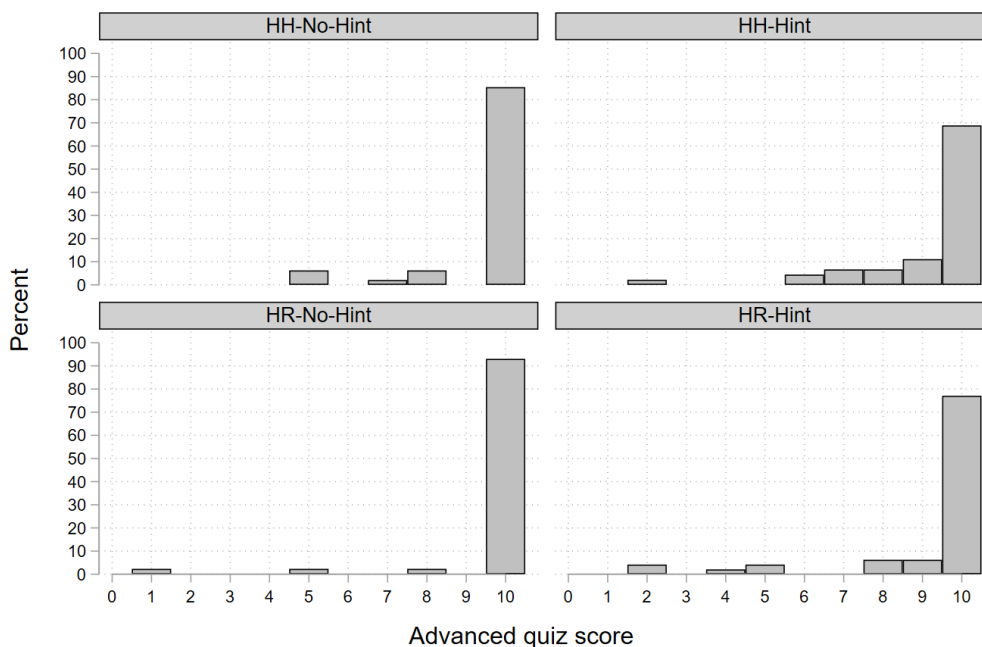


Figure 6 displays the distributions of the scores of Hint Advanced Quiz for HH-

<sup>8</sup> We also compare Basic Quiz scores across treatments using a one-way analysis of variance (ANOVA). There is no statistical difference in Basic Quiz scores across the treatments ( $p = 0.481$ ).

Hint and HR-Hint, as well as those of No-Hint Advanced Quiz for HH-No-Hint and HR-No-Hint. The figure highlights that most subjects in HH-Hint and HR-Hint (69% in HH-Hint and 77% in HR-Hint) attained perfect scores (10 points) in Hint Advanced Quiz. Additionally, most of the other subjects in these treatments scored near the maximum (8 or 9 points). Thus, most subjects in HH-Hint and HR-Hint received hints, which facilitated their understanding of SP. After Hint Advanced Quiz, we distributed the correct answers to each subject in HH-Hint and HR-Hint and explained them using voice software. As this step further enhances the understanding of SP, most subjects in HH-Hint and HR-Hint received hints to understand SP prior to the auction.

As shown in the figure, most subjects in HH-No-Hint and HR-No-Hint (85% in HH-No-Hint and 93% in HR-No-Hint ) attained perfect scores (10 points) in No-Hint Advanced Quiz. Additionally, most of the other subjects in these treatments scored near the maximum (7, 8, or 9 points). As outlined in Subsection 2.3.3, No-Hint Advanced Quiz does not explicitly provide hints about SP, but focuses solely on questions that ask whether the payoffs are positive, negative, or zero. This quiz enabled subjects in HH-No-Hint and HR-No-Hint to comprehend the Vickrey auction rules thoroughly and to recognize that overbidding can causes negative payoffs.

In comparing Advanced Quiz scores across treatments, we employed an OLS regression model, regressing Advanced Quiz scores on four treatment dummies while incorporating robust standard errors. Subsequently, we compared the estimated dummy coefficients using an F test, with results presented through Bonferroni-adjusted p-values. There are no statistically significant differences in Advanced Quiz scores across treatments ( $p = 0.454$ ).<sup>9</sup> This implies that No-Hint Advanced Quiz adjusts the subjects' earnings levels and comprehension levels of the auction rules before the auction in HH-No-Hint and HR-No-Hint similar to those in HH-Hint and HR-Hint.

In summary, most subjects in HH-Hint and HR-Hint had a good understanding of SP in Vickrey auctions by obtaining perfect scores in Hint Advanced Quiz. Additionally,

<sup>9</sup> We also compare Advanced Quiz scores across the four treatments by using one-way ANOVA. There are no statistically significant differences in Advanced Quiz scores across treatments ( $p = 0.444$ ). However, the ratio of the subjects with perfect scores is higher in HH-No-Hint and HR-No-Hint (0.890) than in HH-Hint and HR-Hint (0.731) with a 1% significance level by using two-sample t-tests.

the earnings levels and comprehension levels of the auction rules before the auction in all treatments are well controlled.

### 3.3 Bidding behavior

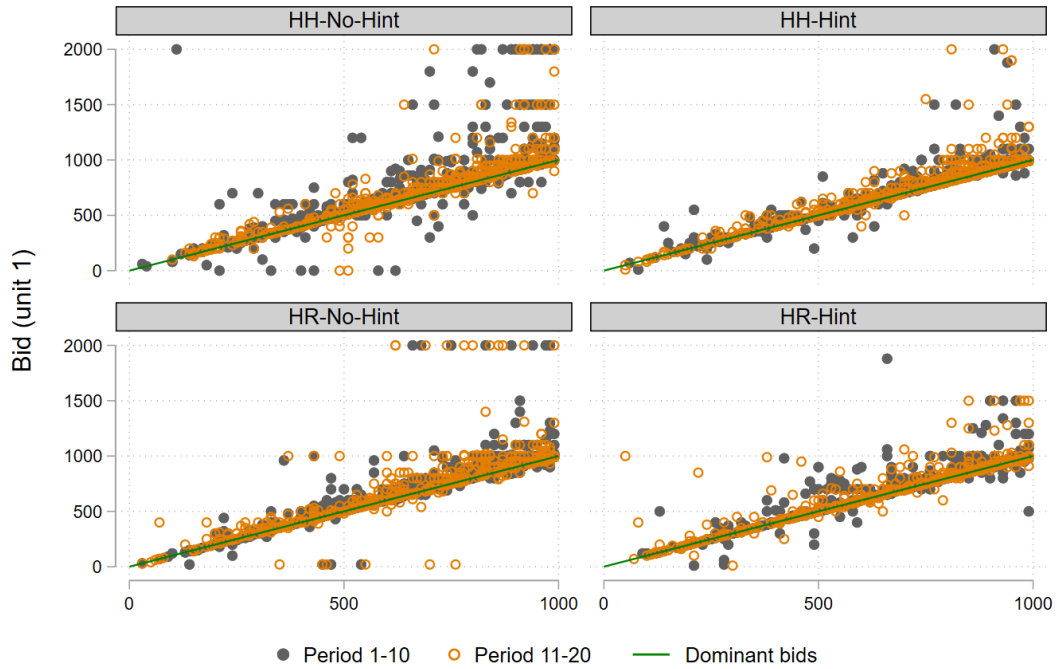
We classify a subject's bids as follows: given subject  $i$ 's valuation,  $v_i^1$  ( $v_i^2$ ) for the first (second) unit, their bid  $b_i^1$  ( $b_i^2$ ) for the first (second) unit is *dominant* if  $b_i^1 = v_i^1$  ( $b_i^2 = v_i^2$ ), *over* if  $b_i^1 > v_i^1$  ( $b_i^2 > v_i^2$ ), and *under* if  $b_i^1 < v_i^1$  ( $b_i^2 < v_i^2$ ). For example, assume that the valuations  $v_i = (v_i^1, v_i^2)$ ,  $i = 1, 2, 3$ , of the three subjects are  $v_1 = (800, 200)$ ,  $v_2 = (600, 400)$ ,  $v_3 = (910, 500)$  and that their bids  $b_i = (b_i^1, b_i^2)$ ,  $i = 1, 2, 3$ , are  $b_1 = (850, 240)$ ,  $b_2 = (600, 450)$ , and  $b_3 = (900, 500)$ . Subsequently, the dominant bids are as follows: bidder 2's bids for the first unit ( $b_2^1 = 600 = v_2^1$ ) and the second unit of bidder 3 ( $b_3^2 = 500 = v_3^2$ ). Overbids are bidder 1's bids for the first and second units ( $b_1^1 = 850 > v_1^1 = 800$  and  $b_1^2 = 240 > v_1^2 = 200$ ) and the second unit of bidder 2 ( $b_2^2 = 450 > v_2^2 = 400$ ). In this example, an underbid is unique and is the first unit of bidder 3 ( $b_3^1 = 900 < v_3^1 = 910$ ). The *dominant bidding rate* is the number of dominant bids divided by the total number of bids. Thus, the dominant bid rates of the subjects  $i = 1, 2, 3$  are 0, 0.5, and 0.5, respectively, and the overall average dominant bid rate is  $2/6 = 1/3 = 33.33\%$ . We primarily use the overall average dominant bid rate for the statistical analysis.

Figure 7 plots the valuations and the corresponding bids for each treatment. Panels (a) and (b) show the data for Units 1 and 2, respectively. Note that dominant bids lie along the  $45^\circ$  green line. The eight graphs in the figure reveal a concentration of valuations and bids on the  $45^\circ$  line, representing dominant bids. The data points located above and below this line indicate overbids and underbids, respectively. Panel (a) shows that some bids for Unit 1 reached a maximum of 2,000. Furthermore, the frequencies of these maximum bids are higher in HH-No-Hint and HR-No-Hint than in HH-Hint and HR-Hint. Conversely, Panel (b) shows that some bids for Unit 2 are at a minimum value of 0, and these minimum bids are also more common in HH-No-Hint and HR-No-Hint than in HH-Hint and HR-Hint.

Figure 8 shows the frequencies of dominant bids, overbids, and underbids for each

Figure 7: Scatter plots between bids and valuation in Rounds 1–10 and 11–20 by treatment and units

(a) Unit 1



(b) Unit 2

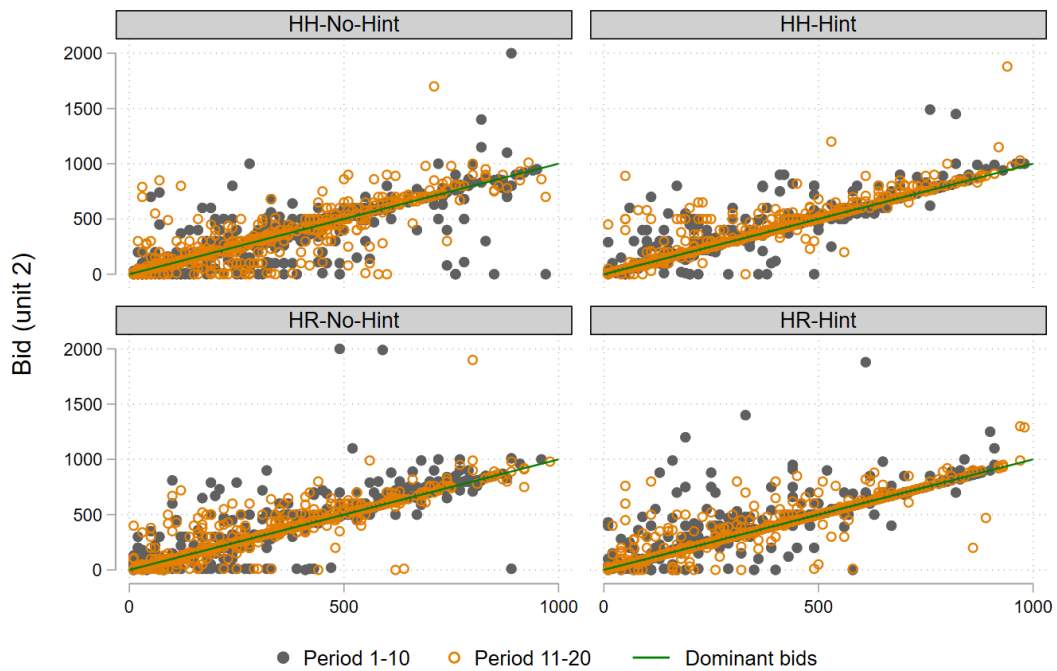
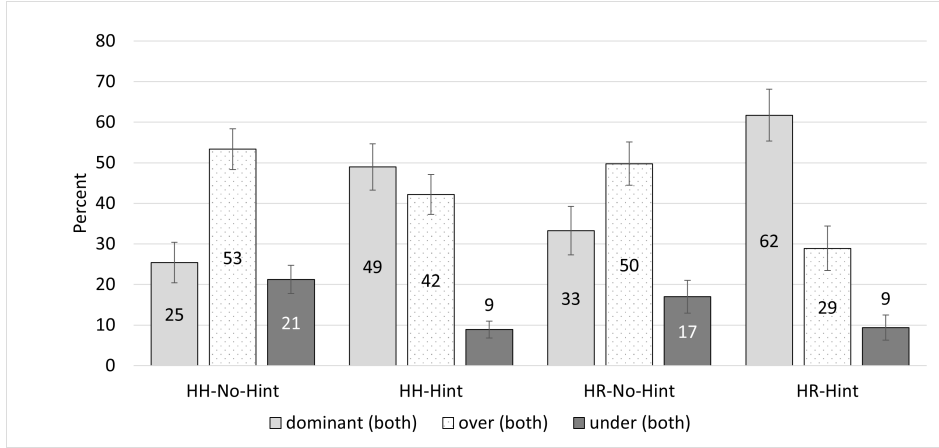
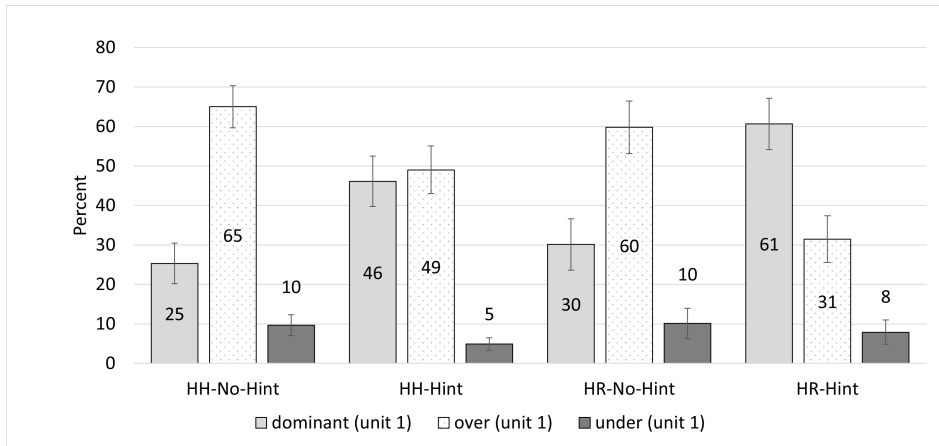


Figure 8: Bid category by treatments and units

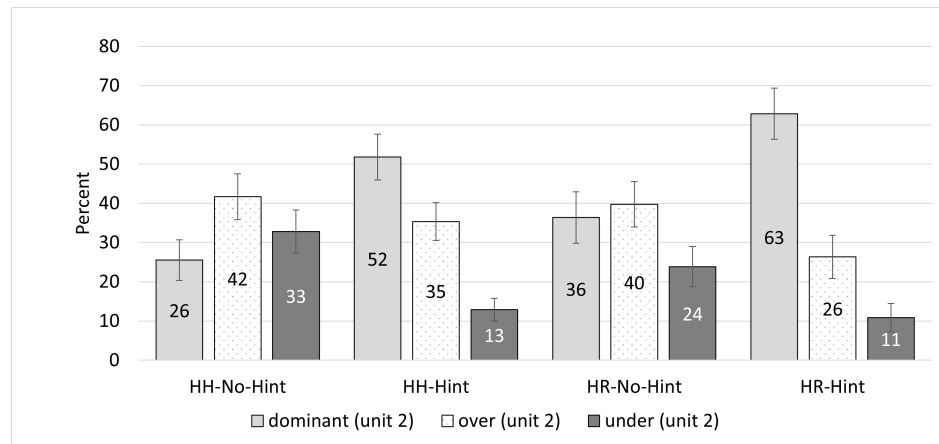
(a) Both units



(b) Unit 1



(c) Unit 2



Notes: The error bars correspond to the standard errors.

treatment.<sup>10</sup> For each subject and each unit, we compute the average dominant bidding rate, overbidding rate, and underbidding rate across all 20 rounds, resulting in one observation per bidding category. Panels (a)–(c) display results of the both, first and second units. HH-No-Hint is the benchmark environment in which no hints about SP are provided, and the subjects bid against human rivals. Panel (a) shows that in this treatment, the total overbidding rate is approximately 53%, and the total dominant and underbidding rates are lower, 25% and 21%, respectively. This observation is consistent with findings in experiments on the multi-unit Vickrey auction by Manelli et al. (2006), Engelmann and Grimm (2009), and Kagel and Levin (2009). Panel (b) illustrates a more pronounced overbidding tendency for the first unit, whereas Panel (c) indicates that this tendency is weaker for the second unit. HR-No-Hint, which excludes the human interaction present in HH-No-Hint, exhibits a tendency similar to HH-No-Hint. This implies that even without the impact of human interaction, such as strategic interaction and social preference, many subjects overbid, and few bid their true valuations. As summarized in Subsection 3.2, most subjects have a good comprehension of Vickrey auction rules. Thus, most subjects in HH-No-Hint and HR-No-Hint overbid, although they have a good comprehension of Vickrey auction rules.

In summary, in the absence of hints about SP, subjects tend to overbid in the Vickrey auction, even when most of them have a good comprehension of Vickrey auction rules, and factors such as strategic interaction and social preference are removed. Thus, overbidding in Vickrey auctions cannot be solely attributed to insufficient comprehension of auction rules or human interaction.

However, the bidding tendencies of HH-Hint and HR-Hint differ. This implies that the hints about SP influenced the subjects' bidding behavior. In Subsection 3.4, we statistically examine this effect.

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<sup>10</sup> We asked subjects how they bid in the auction through a post-experimental survey. We confirmed that there is a positive correlation between their reported bidding behavior in the survey and their actual bidding behavior in the experiments. This suggests that subjects honestly reported their bidding strategies in the survey. For detailed results from the post-experimental survey, please refer to Online Appendix.

### 3.4 Effect of hint on strategy-proofness

Table 2 summarizes the dominant bidding rates for (i) all subjects, (ii) subjects with perfect scores in Advanced Quiz, and (iii) subjects with imperfect scores in Advanced Quiz in each treatment. For each subject and each unit, we compute the average dominant bidding rate across all 20 rounds, yielding one observation per unit per subject. First, to assess whether SP hints have a significant impact on the dominant bid rate, we conducted statistical tests, specifically two-sample t-tests. The summarized findings are as follows:

**Result 1** (*Effect of hints about SP*)

- (i) Hints about SP significantly increase dominant bids in Vickrey auctions when considering data from both units. The mean increase is 23.528% from HH-No-Hint to HH-Hint.
- (ii) The effectiveness of hints persists in HH-No-Hint and HH-Hint when focusing solely on subjects with perfect scores, but not for those with imperfect scores.

To establish (i), Hypothesis 1 is rejected at  $p = 0.003$ . To establish (ii), we analyze data separately for subjects with perfect and imperfect scores in Advanced Quiz. For (ii), Hypothesis 1 is rejected at  $p = 0.002$  for subjects with perfect scores, and supported at  $p = 0.452$  for those with imperfect scores.

**Result 2** (*Effect of hints about SP with robot rivals*)

- (i) In environments with no human interaction (HR-No-Hint and HR-Hint), hints about SP are effective when considering data from both units. The mean increase is 28.463% from HR-No-Hint to HR-Hint.
- (ii) Hints are effective when focusing only on the data of subjects with perfect scores, but not for those with imperfect scores.

We first establish (i). Thus, Hypothesis 2 is rejected at  $p = 0.002$ . For (ii), Hypothesis 2 is rejected at  $p < 0.001$  for subjects with perfect scores, and supported at  $p = 0.669$  for those with imperfect scores.

The results indicate that subjects provided with SP hints via Hint Advanced Quiz have significantly higher rates of dominant bidding. This suggests that understanding

SP is an important factor in dominant bidding. We postulate that the subjects achieving perfect scores in Hint Advanced Quiz possess a better understanding of SP, resulting in higher rates of dominant bids compared to those with imperfect scores. This postulation was statistically tested. In HH-Hint, subjects with perfect scores in Hint Advanced Quiz submit dominant bids more frequently than those with imperfect scores across all data points for both units. The mean increase is 10.392%. Similarly, in HR-Hint, even in the absence of human interaction, perfect scores have a significant impact on the rate of dominant bids. Using all data from both units, the mean increase is 58.544%. These results further support our hypothesis that understanding SP is an important factor in dominant bidding.

### 3.5 Effect of human interaction

Based on the data presented in Table 2, we analyze the effects of human interaction. We summarize our findings on human interaction as follows:

**Result 3** (*Effect of Human interaction with No-Hint Advanced Quiz*)

- (i) Removing human interaction does not significantly influence the increase in the dominant bidding rate in Vickrey auctions when hints about SP are not provided, based on the dataset for both units.
- (ii) Removing human interaction does not significantly influence the increase in the dominant bidding rate in Vickrey auctions among subjects with either perfect or imperfect scores on the No-Hint Advanced Quiz.

We establish (i): Hypothesis 3 is supported at  $p = 0.314$ . Regarding (ii), Hypothesis 3 is supported at  $p = 0.287$  for subjects with perfect quiz scores, and at  $p = 0.896$  for those with imperfect scores.

**Result 4** (*Effect of Human interaction with Hint Advanced Quiz*)

- (i) When hints about SP are provided, removing human interaction does not significantly influence the increase in the dominant bidding rate in Vickrey auctions, again based on the dataset for both units.
- (ii) Eliminating human interaction results in an increased rate of dominant bidding in Vickrey auctions; however, this increase is observed only among subjects who achieved

Table 2: Dominant bidding rates by treatment, Advanced Quiz scores, and unit

Treatments	(1) HH-No-Hint	(2) HH-Hint	(3) HR-No-Hint	(4) HR-Hint	(3) – (1)	(4) – (2)
(a)Both units						
All	0.254	<*** 0.489	0.333	<*** 0.617	0.078	0.128
(S.E.)	(0.050)	(0.057)	(0.060)	(0.064)		
obs.	48	45	43	48		
Perfect score	0.249	<*** 0.522	0.339	<*** 0.751	0.089	0.230**
(S.E.)	(0.054)	(0.069)	(0.063)	(0.064)		
obs.	41	31	40	37		
Imperfect score	0.282	< 0.418	0.250	> 0.166	-0.032	-0.252*
(S.E.)	(0.138)	(0.104)	(0.161)	(0.090)		
obs.	7	14	3	11		
(b)Unit 1						
All	0.253	<** 0.461	0.301	<*** 0.606	0.048	0.145
(S.E.)	(0.051)	(0.064)	(0.065)	(0.065)		
obs.	48	45	43	48		
Perfect score	0.248	<*** 0.508	0.295	<*** 0.736	0.047	0.228**
(S.E.)	(0.056)	(0.080)	(0.067)	(0.067)		
obs.	41	31	40	37		
Imperfect score	0.286	< 0.357	0.383	> 0.168	0.098	-0.189
(S.E.)	(0.133)	(0.104)	(0.311)	(0.089)		
obs.	7	14	3	11		
(c)Unit 2						
All	0.255	<*** 0.518	0.364	<*** 0.628	0.109	0.110
(S.E.)	(0.052)	(0.058)	(0.066)	(0.065)		
obs.	48	45	43	48		
Perfect score	0.251	<*** 0.535	0.383	<*** 0.766	0.131	0.231**
(S.E.)	(0.056)	(0.069)	(0.070)	(0.065)		
obs.	41	31	40	37		
Imperfect score	0.279	< 0.479	0.117	< 0.164	-0.162	-0.315**
(S.E.)	(0.149)	(0.110)	(0.073)	(0.091)		
obs.	7	14	3	11		

Notes: a) We compare the dominant bidding rates between treatments using two sample t-tests. b) \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. c) Numbers in parentheses are standard errors. d) The unit of observations is the subject. The total number of observations is the total number of subjects in each treatment.

perfect scores on the Hint Advanced Quiz. No such increase is found among those with imperfect scores.

We first establish (i): Hypothesis 4 is supported at  $p = 0.142$ . Regarding (ii), Hypothesis 4 is rejected at  $p = 0.017$  for subjects with perfect quiz scores. For those with imperfect scores, it is also rejected at  $p = 0.090$ , in a direction contrary to our expectations.

The results in this subsection imply that human interaction is also a non-negligible factor in dominant bidding, particularly among subjects who understand the SP. In particular, human interactions and understanding SP affect the rate of dominant bidding. Thus, our findings suggest that various factors, including human interactions and differing levels of understanding SP, cause dominated bidding in Vickrey auctions.

### 3.6 Learning Effect

Table 3 summarizes the dominant bidding rates for (i) the first round, (ii) the first ten rounds, and (iii) the last ten rounds of each treatment. We statistically test whether SP hints increase the dominant bid rate during the first round by conducting two sample t-tests.

#### **Result 5** (*First round*)

(i) Hints about SP increase the dominant bids in the Vickrey auctions in the first round. The mean increase is 25.000% from HH-No-Hint to HH-Hint.

(ii) In environments with no human interaction (i.e., in HR-No-Hint and HR-Hint), hints about SP are effective in the first round. The mean increase is 31.347% from HR-No-Hint to HR-Hint.

(iii) Hints are effective when focusing only on the data of the subjects with perfect scores. However, they are ineffective when focusing only on subjects with imperfect scores.

The results indicate that subjects provided with SP hints have significantly higher rates of dominant bidding in the first round. This suggests that an understanding of SP is an important factor in dominant bidding, even if the bidders do not have much experience with auctions.

We use two-sample t-tests to statistically test whether learning leads to increased dominant bid rates by comparing the rates between the first and last 10 rounds.

**Result 6** (*Learning effect*)

(i) There is no significant difference in dominant bidding rates between the first and last 10 rounds in all treatments ( $p = 0.557$  for HH-No-Hint;  $p = 0.952$  for HH-Hint;  $p = 0.135$  for HR-No-Hint;  $p = 0.186$  for HR-Hint).

(ii) Focusing only on the data of the subjects with perfect scores, there is no significant difference in dominant bidding rates between the first and last 10 rounds in HH-No-Hint ( $p = 0.596$ ), HH-Hint ( $p = 0.700$ ) and HR-No-Hint ( $p = 0.135$ ). There is a 5% significant difference in HR-Hint.

(iii) Focusing only on the data of the subjects with imperfect scores, there is no significant difference in dominant bidding rates between the first and last 10 rounds in all treatments ( $p = 0.818$  for HH-No-Hint;  $p = 0.583$  for HH-Hint;  $p = 0.839$  for HR-Hint).<sup>11</sup>

The results indicate that subjects do not increase their dominant bidding over time, except for those who achieved a perfect score on the Hint Advanced Quiz. This suggests that while an understanding of SP is an important factor in dominant bidding, learning becomes effective in increasing dominant bidding rates only after subjects have understood SP.

### 3.7 Regression analysis of dominant bidding

We conducted a logistic regression analysis to examine the treatment effect on dominant bidding. The analysis uses a dominant bidding dummy variable as the dependent variable, which takes the value of 1 if the subject bids her true valuations in a given round and 0 otherwise. The independent variables include an SP hint dummy (SP hint), which is set to 1 for treatments where Hint Advanced Quiz is administered to the subjects, and a robot dummy, which is set to 1 for treatments involving robot rivals. We also included a control variable, a perfect score dummy, which takes the value of 1 if subjects achieved a perfect score on Advanced Quiz, and Round, which ranges from 1 to 20. We

<sup>11</sup> In HR-No-Hint, the mean and standard error of dominant bidding rates among imperfect score subjects between (b) Former 10 rounds and (c) Latter 10 rounds are identical; there is no difference to test.

Table 3: Dominant bidding rates of both units by treatment, Advanced Quiz scores and rounds

Treatments	(1)		(2)	(3)		(4)	(3) – (1)	(4) – (2)
	HH-No-Hint		HH-Hint	HR-No-Hint		HR-Hint		
(a) Round 1								
All	0.250	<***	0.500	0.291	<***	0.604	0.041	0.104
(S.E.)	(0.054)		(0.069)	(0.058)		(0.068)		
obs.	48		45	43		48		
Perfect score	0.244	<***	0.532	0.288	<***	0.716	0.044	0.184*
(S.E.)	(0.058)		(0.083)	(0.062)		(0.071)		
obs.	41		31	40		37		
Imperfect score	0.286	<	0.429	0.333	>	0.227	–0.048	–0.201
(S.E.)	(0.149)		(0.127)	(0.167)		(0.124)		
obs.	7		14	3		11		
(b) Former 10 rounds								
All	0.247	<***	0.489	0.322	<***	0.604	0.075	0.115
(S.E.)	(0.049)		(0.060)	(0.058)		(0.064)		
obs.	48		45	43		48		
Perfect score	0.243	<***	0.526	0.328	<***	0.732	0.085	0.207**
(S.E.)	(0.053)		(0.074)	(0.061)		(0.064)		
obs.	41		31	40		37		
Imperfect score	0.271	<	0.407	0.250	>	0.173	–0.021	–0.234
(S.E.)	(0.134)		(0.105)	(0.161)		(0.101)		
obs.	7		14	3		11		
(c) Latter 10 rounds								
All	0.261	<***	0.490	0.343	<***	0.630	0.082	0.140
(S.E.)	(0.053)		(0.056)	(0.063)		(0.065)		
obs.	48		45	43		48		
Perfect score	0.256	<***	0.518	0.350	<***	0.770	0.094	0.253***
(S.E.)	(0.058)		(0.066)	(0.066)		(0.064)		
obs.	41		31	40		37		
Imperfect score	0.293	<	0.429	0.250	>	0.159	–0.043	–0.269*
(S.E.)	(0.155)		(0.107)	(0.161)		(0.090)		
obs.	7		14	3		11		
(c) Latter 10 rounds – (b) Former 10 rounds								
All	0.015		0.001	0.021		0.026		
Perfect score	0.013		–0.008	0.023		0.038**		
Imperfect score	0.021		0.021	0		–0.014		

Notes: a) We compare the dominant bidding rates between treatments using two-sample t-tests. b) \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. c) Numbers in parentheses are standard errors. d) The unit of observations is the subject. The total number of observations is the number of subjects in each treatment.

clustered the robust standard errors at the individual level. The results of Unit 1, Unit 2, and both units are summarized in Table 4.

The logistic regression results demonstrate that the SP hint dummy has a statistically significant positive impact on dominant bidding—administering Hint Advanced Quiz enhances dominant bidding. The perfect score dummy also has a significant positive impact on dominant bidding. These results confirm the conclusion drawn in Subsection 3.4 that understanding SP is an important factor in dominant bidding. However, the robot dummy is not statistically significant, indicating that the human interaction factor does not significantly affect dominant bidding. This contradicts the conclusion in Subsection 3.5. In our logistic regression analysis, the human interaction factor is not as robust as the understanding of SP. Additionally, the round variable is not statistically significant, indicating that learning does not significantly affect dominant bidding. This is consistent with the results presented in Subsection 3.6.

Next, we performed a regression analysis to examine the impact of the subjects' performance in Advanced Quiz, with and without hints, on dominant bidding. We conducted an OLS linear regression, considering average dominant bids for Units 1 and 2, as well as both units collectively, with robust standard errors. The dependent variable is the average rate of dominant bids, which ranges from 0 to 1. The independent variables included the Advanced Quiz scores, which range from 0 to 10, and a dummy variable for treatments with robot rivals, referred to as the robot dummy. The results are summarized in Table 5, organized by Advanced Quiz type and units.

The results indicate that higher scores in Hint Advanced Quiz are associated with more frequent dominant bidding in Units 1 and 2, as well as when both units are combined. However, the scores in No-Hint Advanced Quiz do not seem to influence the rate of dominant bids. Based on these findings, we suggest that our design of Hint Advanced Quiz effectively enhances dominant bidding and serves as a reliable method for measuring the level of understanding of SP in Vickrey auctions.

The OLS results indicate that higher scores in Hint Advanced Quiz are associated with more frequent dominant bidding in Units 1 and 2 as well as when both units are combined. Nevertheless, the scores in No-Hint Advanced Quiz do not appear to

Table 4: Regression analysis of treatment dummy on dominant bidding

	Both			Unit 1			Unit 2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SP hint	1.034*** (0.347)	1.230*** (0.375)	1.230*** (0.375)	0.926** (0.371)	1.110*** (0.399)	1.110*** (0.399)	1.142*** (0.356)	1.351*** (0.389)	1.351*** (0.389)
Robot	0.380 (0.374)	0.320 (0.381)	0.321 (0.382)	0.240 (0.408)	0.181 (0.419)	0.181 (0.419)	0.513 (0.390)	0.454 (0.395)	0.454 (0.395)
SP hint $\times$ Robot	0.140 (0.513)	0.138 (0.517)	0.138 (0.517)	0.347 (0.552)	0.351 (0.557)	0.351 (0.558)	-0.060 (0.531)	-0.067 (0.536)	-0.067 (0.536)
Perfect score		1.040*** (0.370)	1.040*** (0.370)		1.012** (0.402)	1.012** (0.402)		1.071*** (0.378)	1.071*** (0.378)
Round			0.006 (0.004)			0.008 (0.006)			0.005 (0.005)
Constant	-1.077*** (0.262)	-1.998*** (0.457)	-2.063*** (0.457)	-1.082*** (0.270)	-1.978*** (0.479)	-2.060*** (0.482)	-1.071*** (0.270)	-2.021*** (0.472)	-2.069*** (0.471)
Obs.	7,360	7,360	7,360	3,680	3,680	3,680	3,680	3,680	3,680
Cluster	184	184	184	184	184	184	184	184	184
Wald Chi2	20.71	26.58	29.86	18.85	22.74	24.68	20.15	25.82	28.50
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: a) We conducted logit regression on the dominant bidding dummy, considering the SP hint dummy and robot dummy, conditional on the Advanced Quiz perfect score dummy, with robust standard errors clustered at the individual level. b) Dominant bidding dummy equals 1 if subjects submitted a dominant bid in a round and 0 otherwise. SP hint dummy equals 1 if subjects take Hint Advanced Quiz and 0 if they take No-Hint Advanced Quiz. Robot dummy equals 1 if subjects compete against robot rivals and 0 if they compete against human rivals. Perfect score equals 1 if subjects get a perfect score in Advanced Quiz and 0 otherwise. Round ranges from 1 to 20. c) \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. d) Numbers in parentheses are standard errors. e) The total number of observations is the number of subjects  $\times$  number of rounds  $\times$  number of units in each treatment.

Table 5: Regression analysis of Advanced Quiz scores on average dominant bids

	w/ hints			w/o hints		
	Both	Unit 1	Unit 2	Both	Unit 1	Unit 2
	(1)	(2)	(3)	(4)	(5)	(6)
Advanced Quiz score	0.078*** (0.016)	0.081*** (0.016)	0.076*** (0.017)	0.005 (0.016)	-0.006 (0.024)	0.016 (0.017)
Robot	0.132 (0.082)	0.150* (0.087)	0.114 (0.084)	0.078 (0.078)	0.049 (0.084)	0.107 (0.084)
Constant	-0.230 (0.160)	-0.281* (0.154)	-0.178 (0.171)	0.205 (0.157)	0.309 (0.228)	0.101 (0.172)
Obs.	93	93	93	91	91	91
R-squared	0.140	0.137	0.122	0.012	0.004	0.023

*Notes:* a) We conducted OLS linear regression on the average dominant bids for units 1 and 2, as well as both units collectively, regressed on Advanced Quiz scores with robust standard errors. b) Average dominant bids indicate the mean of dominant bidding over 20 rounds for each subject, ranging from 0 to 1. Advanced Quiz scores range from 0 to 10. Hint Advanced Quiz scores are used in Model (1-3), and No-Hint Advanced Quiz are used in Model (4-6). Robot dummy is 1 if subjects compete against robot rivals and 0 if subjects compete against human rivals. c) \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. d) Numbers in parentheses are standard errors. e) The total number of observations is the number of subjects in HH-Hint & HR-Hint or in HH-No-Hint & HR-No-Hint.

influence the rate of dominant bids. As confirmed in Subsection 3.2, there is no statistical difference in the earnings levels and comprehension levels of the auction rules between Hint Advanced Quiz and No-Hint Advanced Quiz. Thus, these results confirm the conclusion that understanding SP is an important factor in dominant bidding. However, the robot dummy is not statistically significant, except for in Unit 1 of HH-Hint & HR-Hint (10%). Similar to the logistic regression analysis, our OLS analysis suggests that the human interaction factor is not as robust as the understanding of SP. Notably, our OLS analysis further indicates that our design of Hint Advanced Quiz effectively enhances dominant bidding and serves as a reliable method for measuring the level of understanding of SP in Vickrey auctions.

### 3.8 Degree of Deviation from True Value

We defined dominant bidding strictly as bidding exactly equal to one's valuation. In this section, we calculate bidder  $i$ 's degree of deviation from the true value, denoted as  $D_i^u$ , for each unit  $u$  in each round. The deviation is defined as the absolute difference

between the bid and the corresponding true value, computed as follows:

$$D_i^u = |b_i^u - v_i^u|$$

In each round, we compute the average deviation across the two units as:

$$\bar{D}_i = \frac{1}{2} (|b_i^1 - v_i^1| + |b_i^2 - v_i^2|)$$

where  $b_i^1$  and  $b_i^2$  denote bidder  $i$ 's bids for units 1 and 2, respectively, and  $v_i^1$  and  $v_i^2$  denote the corresponding true values for units 1 and 2. Table 6 summarizes the degree of deviation from the true value for both units, unit 1 and unit 2, across treatments and advanced quiz scores.

**Result 7** (*Effect of hints about SP*)

- (i) Hints about SP significantly decrease the degree of deviation of submitted bids from the true value in Vickrey auctions when considering data from both units.
- (ii) The effectiveness of hints persists in HH-No-Hint and HH-Hint when focusing solely on subjects with perfect scores, but not among those with imperfect scores.

To establish (i), Hypothesis 1 is rejected at  $p = 0.002$ . To establish (ii), we analyze the data separately for subjects with perfect and imperfect scores in the Advanced Quiz. For (ii), Hypothesis 1 is rejected at  $p = 0.003$  for subjects with perfect scores and supported at  $p = 0.222$  for those with imperfect scores.

**Result 8** (*Effect of hints about SP with robot rivals*)

- (i) In environments without human interaction (HR-No-Hint and HR-Hint), hints about SP are not effective in decreasing the degree of deviation from the true value when considering data from both units.
- (ii) Hints are effective when focusing only on subjects with perfect scores, but not among those with imperfect scores.

We first establish (i). Thus, Hypothesis 2 is supported at  $p = 0.107$ . For (ii), Hypothesis 2 is rejected at  $p = 0.002$  for subjects with perfect scores and supported at  $p = 0.506$  for those with imperfect scores.

**Result 9** (*Effect of human interaction with No-Hint Advanced Quiz*)

(i) Removing human interaction does not significantly influence the degree of deviation from the true value in Vickrey auctions when hints about SP are not provided, based on the dataset for both units.

(ii) Removing human interaction does not significantly influence the degree of deviation from the true value in Vickrey auctions among subjects with either perfect or imperfect scores on the No-Hint Advanced Quiz.

We establish (i): Hypothesis 3 is supported at  $p = 0.274$ . Regarding (ii), Hypothesis 3 is supported at  $p = 0.353$  for subjects with perfect quiz scores and at  $p = 0.616$  for those with imperfect scores.

**Result 10** (*Effect of human interaction with Hint Advanced Quiz*)

(i) When hints about SP are provided, removing human interaction does not significantly influence the degree of deviation from the true value in Vickrey auctions, again based on the dataset for both units.

(ii) Removing human interaction does not significantly influence the degree of deviation from the true value in Vickrey auctions among subjects with perfect scores; however, an increased degree of deviation from the true value is observed among subjects who achieved imperfect scores on the Hint Advanced Quiz.

We first establish (i): Hypothesis 4 is supported at  $p = 0.913$ . Regarding (ii), Hypothesis 4 is supported at  $p = 0.109$  for subjects with perfect quiz scores. For those with imperfect scores, it is rejected at  $p = 0.092$ , in a direction contrary to our expectations.

SP hints exert a positive influence on subjects with perfect scores, leading them to deviate less from the true values. However, this effect is not observed among subjects with imperfect scores.

Table 6: Degree of Deviation from True Value

Treatments	(1)	(2)	(3)	(4)	(3) – (1)	(4) – (2)
	HH-No-Hint	HH-Hint	HR-No-Hint	HR-Hint		
(a) Both units						
All	96.750	>*** 50.067	77.471	> 48.438	–19.279	–1.629
(S.E)	(11.413)	(8.795)	(13.445)	(11.800)		
obs.	48	45	43	48		
Perfect Scores	94.811	>*** 43.218	76.944	>*** 23.689	–17.867	–19.529
(S.E)	(12.623)	(9.155)	(14.421)	(7.894)		
obs.	41	31	40	37		
Imperfect Scores	108.107	> 65.232	84.500	< 131.682	–23.607	66.450*
(S.E)	(27.375)	(19.689)	(17.678)	(34.647)		
obs.	7	14	3	11		
(b) Unit 1						
All	111.458	>*** 50	84.93	>*** 43.271	–26.528	6.729
(S.E)	(16.515)	(10.768)	(19.244)	(12.220)		
obs.	48	45	43	48		
Perfect Scores	111.366	>*** 38.597	83.525	>*** 18.324	–27.840	–20.272*
(S.E)	(18.489)	(9.685)	(20.388)	(6.450)		
obs.	41	31	40	37		
Imperfect Scores	112	> 75.25	103.667	< 127.182	–8.333	51.932
(S.E)	(36.092)	(26.664)	(56.628)	(40.562)		
obs.	7	14	3	11		
(c) Unit 2						
All	82.042	>** 50.133	70.012	> 53.604	–12.030	3.471
(S.E)	(11.165)	(9.203)	(11.605)	(12.682)		
obs.	48	45	43	48		
Perfect Scores	78.256	>** 47.839	70.363	>** 29.054	–7.894	18.785
(S.E)	(11.036)	(10.810)	(12.381)	(10.765)		
obs.	41	31	40	37		
Imperfect Scores	104.214	> 55.214	65.333	<* 136.182	–38.881	80.968**
(S.E)	(42.938)	(17.927)	(25.859)	(31.789)		
obs.	7	14	3	11		

Notes: (a) We compare the average degree of deviation between treatments using two sample t-tests. c) \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. d) Numbers in parentheses are standard errors. e) The unit of observations is the subject. The total number of observations is the total number of subjects in each treatment.

## 4 Efficiency, bidders' payoffs, and seller's total revenue

### 4.1 Efficiency measure

We follow Kagel and Levin (2009)'s efficiency measure. For the details of the efficiency measures, please refer to Masuda et al. (2022). In each round, if bidders  $i$  and  $j$  are, respectively, the winners with the first and second highest bids, then the *efficiency* is

given by

$$r = \begin{cases} (v_i^1 + v_j^1) \setminus (v[1] + v[2]) & \text{if } i \neq j \\ (v_i^1 + v_i^2) \setminus (v[1] + v[2]) & \text{if } i = j \end{cases},$$

where  $v[1]$  and  $v[2]$  denote the two highest valuations among  $\{v_1^1, v_1^2, v_2^1, v_2^2, v_3^1, v_3^2\}$ .<sup>12</sup>

We apply the above efficiency formula to calculate the efficiencies of HH-No-Hint and HH-Hint, where the experiments involve only human bidders, which we refer to as *observed efficiency*. In the auctions of HR-No-Hint and HR-Hint, two of the three bidders are robot bidders, whose bids are automatically generated from a specified probability distribution. It does not make sense to compute efficiency by using the bid data of robot bidders. Thus, to calculate the efficiency of HR-No-Hint and HR-Hint only for the bid data of human subjects, we conduct simulations as explained in Subsection 4.2. We refer to the simulation results as *simulated efficiency*.

We divide the dataset into two parts: one containing subjects with perfect scores in Advanced Quiz and the other containing subjects with imperfect scores in Advanced Quiz. Subsequently, we calculate the simulated efficiencies of each part of the data. Thus, we analyze the efficiency when only subjects with perfect scores are matched with each other, as well as when only subjects with imperfect scores are matched.

## 4.2 Simulation method

In each treatment, let  $G$  be the largest integer, such that  $3 * G$  is less than or equal to the number of subjects in the treatment group. For example, if the number of subjects in the treatment is 43, as in HR-No-Hint, then  $G = 14$  and  $3 * G = 42$ . For each treatment and each round  $t$  of the experiment, we calculate the *simulated efficiency*, *simulated bidders' payoffs*, and *simulated seller's total revenue* using the following steps:

*Step 1:* We randomly draw  $3 * G$  subjects from the human subjects in the treatment group and match them into  $G$  groups, each of which comprises three subjects. The groups are named  $1, \dots, G$ .

*Step 2:* In each group  $g \in \{1, \dots, G\}$ , we have three subjects with valuations of the two units observed in round  $t$ , that is,  $(v_{1gt}^1, v_{1gt}^2, v_{2gt}^1, v_{2gt}^2, v_{3gt}^1, v_{3gt}^2)$ . Let  $v_{gt}[1]$  and  $v_{gt}[2]$  be

<sup>12</sup> It might be the case that  $i = j$  when one bidder's two bids are the first and second highest. Ties are broken with equal probability.

the first- and second-highest valuations among  $\{v_{1gt}^1, v_{1gt}^2, v_{2gt}^1, v_{2gt}^2, v_{3gt}^1, v_{3gt}^2\}$ .

*Step 3:* In each group  $g \in \{1, \dots, G\}$ , we also have the submitted bids of the three subjects observed in round  $t$ . In other terms,  $(b_{1gt}^1, b_{1gt}^2, b_{2gt}^1, b_{2gt}^2, b_{3gt}^1, b_{3gt}^2)$ . Let bidders  $i$  and  $j$  be the winners, with the first and second highest bids among  $\{b_{1gt}^1, b_{1gt}^2, b_{2gt}^1, b_{2gt}^2, b_{3gt}^1, b_{3gt}^2\}$ . Ties are broken with equal probability.

*Step 4:* In each group  $g \in \{1, \dots, G\}$ , we calculate efficiency  $r_{gt}$  in round  $t$  as follows:

$$r_{gt} = \begin{cases} (v_{igt}^1 + v_{jgt}^1) / (v_{gt}[1] + v_{gt}[2]) & \text{if } i \neq j \\ (v_{igt}^1 + v_{igt}^2) / (v_{gt}[1] + v_{gt}[2]) & \text{if } i = j \end{cases},$$

We also calculate the bidders' payoffs and seller's total revenue from round  $t$ .

*Step 5:* We compute the efficiency averaged across all groups and rounds as follows:  $r = \frac{1}{G \times 20} \sum_{t=1}^{20} \sum_{g=1}^G r_{gt}$ . We also compute the mean of the bidders' payoffs and seller's total revenue for all groups and rounds.

*Step 6:* We repeat Steps 1–5 1,000 times—we perform bootstrap sampling 1,000 times. Subsequently, we obtain the efficiency, the bidders' payoffs, and the seller's total revenue for each bootstrap sample  $B = 1, 2, 3, \dots, 1,000$ , where  $B$  is the bootstrap sampling index.

*Step 7:* We calculate simulated efficiency, which is the the mean efficiency of all bootstrap sampling by  $\frac{1}{1,000} \sum_{B=1}^{1,000} r_B$ , and its bootstrapped standard error by taking the standard deviation of the bootstrap results. This means we first calculate the statistic (e.g., the mean) for each bootstrap sample, and then compute the standard deviation of those 1000 bootstrap estimates.

*Step 8:* We then similarly calculate the simulated bidders' payoffs, the simulated seller's total revenue, and their mean and bootstrapped standard errors. We also calculate the simulated bidders' payoffs for subjects with perfect and imperfect scores in Advanced Quiz, and with their bootstrapped standard errors.

*Step 9:* For each bootstrap iteration, we calculate the mean simulated efficiency. For each treatment, this yields a distribution of 1,000 mean simulated efficiency values. We then compare mean simulated efficiency between treatments using an unpaired t-test. We also compare the mean of simulated bidders' payoffs and mean of simulated seller's total revenue between treatments using an unpaired t-test.

### 4.3 Efficiency: observed and simulated

Table 7 summarizes the results for the observed and simulated efficiencies. Overall, the observed efficiency is higher for HH-Hint (0.992), where subjects are given Hint Advanced Quiz compared to HH-No-Hint (0.984). The simulated efficiencies of HH-No-Hint (0.982) and HH-Hint (0.990) exhibit similar trends. The simulated efficiencies in HR-No-Hint (0.983) and HR-Hint (0.982) are closer, although the difference is statistically significant at the 1% level.

These results suggest a mixed effect of the SP hint on efficiency. To more clearly investigate whether perfect and imperfect scores matter for efficiency, we separate the dataset into two groups: subjects with perfect scores on the Advanced Quiz and subjects with imperfect scores. We then calculate simulated efficiency using these separated datasets. Accordingly, in the simulation, subjects with perfect scores are always matched with other perfect-score subjects, whereas subjects with imperfect scores are always

Table 7: Efficiency by treatment and Advanced Quiz scores: observed and simulated

Treatments	(1)	(2)	(3)	(4)	(3) – (1)	(4) – (2)
	HH-No-Hint	HH-Hint	HR-No-Hint	HR-Hint		
(a) Observed efficiency						
All	0.984	<** 0.992				
	(0.003)	(0.002)				
obs.	320	300				
(b) Simulated efficiency						
All	0.982	<*** 0.990	0.983	>*** 0.982	0.001***	–0.008***
	(0.002)	(0.002)	(0.003)	(0.002)		
obs.	320,000	300,000	280,000	320,000		
Only perfect score matched	0.984	<*** 0.991	0.983	<*** 0.993	–0.002***	0.002***
	(0.002)	(0.002)	(0.002)	(0.001)		
obs.	260,000	200,000	260,000	240,000		
Only imperfect Score matched	0.970	<*** 0.988	0.990	>*** 0.951	0.019***	–0.037***
	(0.009)	(0.004)	(0.000)	(0.009)		
obs.	40,000	80,000	20,000	60,000		
bootstrapped size	1000	1000	1000	1000		

*Notes:* a) We compare the observed efficiencies between treatments using unpaired two-sample t-tests. We compare 1000 bootstrap means of simulated efficiencies between treatments using unpaired two-sample t-tests. b) \* \*\* and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. c) Numbers in parentheses are standard errors for efficiency and bootstrapped standard errors for simulated efficiency. d) For efficiency, the total number of observations is the number of groups  $\times$  20 rounds in each treatment. For simulated efficiency, the total number of simulated observations is the number of simulated groups in each treatment  $\times$  20 rounds  $\times$  1,000 bootstraps.

matched with other imperfect-score subjects. This approach allows us to examine how efficiency changes when subjects are matched only with others who share the same score type.

For the dataset of subjects with perfect scores in Advanced Quiz, the simulated efficiencies are higher when Hint Advanced Quiz is taken than when No-Hint Advanced Quiz is taken—higher in HH-Hint (0.991) than in HH-No-Hint (0.984) and higher in HR-Hint (0.993) than in HR-No-Hint (0.983). This implies that SP hints consistently increase the efficiency of subjects with perfect scores in Advanced Quiz.

Conversely, for subjects with imperfect scores in Advanced Quiz, while the simulated efficiency in HH-Hint (0.988) is higher than that in HH-No-Hint (0.970), it is lower in HR-Hint (0.951) than in HR-No-Hint (0.990). In particular, simulated efficiency in HR-Hint is notably low, which accounts for the overall low simulated efficiency of all subjects in HR-Hint.

#### **4.4 Bidder’s payoff and seller’s total revenue: observed and simulated**

Table 8 summarizes the results for observed bidders’ payoffs and sellers’ total revenue and simulated bidders’ payoffs and sellers’ total revenue. Overall, the observed bidders’ payoffs are higher in HH-Hint (152.044) than in HH-No-Hint (143.490), although the difference is not statistically significant.

For the simulation results, the impact of SP hints on the simulated bidders’ payoffs are mixed. When their rivals are humans, subjects who take Advanced Quiz receive lower payoffs in HH-Hint (145.455) than those who take No-Hint Advanced Quiz in HH-No-Hint (147.978). However, this trend is reversed when the rivals are robots in HR-No-Hint (139.638) and HR-Hint (148.560).

In the simulation, subjects with perfect scores can be matched with other subjects who either have or do not have perfect scores. We then analyze the payoffs of perfect-score and imperfect-score subjects as a function of their Advanced Quiz scores, revealing distinct patterns. Subjects with perfect scores in Hint Advanced Quiz earn higher payoffs (149.522 in HH-Hint; 156.377 in HR-Hint ) than those with perfect scores in No-Hint Advanced Quiz (147.316 in HH-No-Hint; 140.757 in HR-No-Hint ), irrespective

of whether they face human or robot rivals. Conversely, subjects with imperfect scores experience reversed outcomes and receive low payoffs (122.398) in HR-Hint.

Overall, the observed seller's total revenue is higher in HH-Hint (1117.333) than in HH-No-Hint (1098.531), although the difference is not statistically significant. For the simulation results, the impacts of SP hints on the simulated seller's total revenue are mixed, and the patterns are reversed for bidders' payoffs. In other words, SP hints increase simulated seller's total revenue when bidders face human rivals (1084.447 in HH-

Table 8: Bidder's payoffs and seller's total revenues by treatment and Advanced Quiz Score: observed and simulated

Treatments	(1) HH-No-Hint	(2) HH-Hint	(3) HR-No-Hint	(4) HR-Hint	(3) - (1)	(4) - (2)
(a) Observed bidder's payoff						
All	143.490 (6.975)	< 152.044 (7.137)	155.419 (7.393)	< 157.969 (7.121)	11.929	5.924
obs.	960	900	860	960		
Perfect score	142.707 (7.337)	< 157.807 (8.826)	156.913 (7.702)	< 167.757 (7.903)	14.205	9.950
obs.	820	620	800	740		
Imperfect score	148.071 (21.070)	> 139.286 (12.000)	135.5 (26.257)	> 125.286 (15.923)	-12.571	-14.240
obs.	140	280	60	220		
(b) Simulated bidder's payoff						
All	147.978 (4.319)	>*** 145.455 (4.040)	139.638 (4.360)	<*** 148.560 (3.972)	-8.340***	3.105***
obs.	960,000	900,000	840,000	960,000		
Perfect score	147.316 (5.009)	<*** 149.522 (5.476)	140.757 (4.668)	<*** 156.377 (4.937)	-6.559***	6.816***
obs.	820,000	620,000	780,000	740,000		
Imperfect score	151.855 (14.527)	>*** 136.449 (8.777)	124.705 (20.927)	>*** 122.398 (11.184)	-27.150***	-14.051***
obs.	140,000	280,000	60,000	220,000		
(c) Observed seller's total revenue						
All	1098.531 (21.298)	< 1117.333 20.620				
obs.	320	300				
(d) Simulated seller's total revenue						
All	1084.447 (35.046)	<*** 1128.005 (36.271)	1126.575 (36.444)	>*** 1091.301 (35.085)	41.813***	-37.234***
obs.	320,000	300,000	280,000	320,000		

*Notes:* a) We compare the bidder's payoff, simulated bidder's payoff, seller's total revenue, and simulated seller's total revenue between treatments using two-sample t-tests. b) \* \*\* and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. c) Numbers in parentheses are standard errors for efficiency and bootstrapped standard errors for simulated efficiency. d) For bidder's payoff, the total number of observations is the number of bidders in each group  $\times$  20 rounds in each treatment. For seller's total revenue, the total number of observations is the number of groups  $\times$  20 rounds in each treatment. For simulated bidder's payoff and simulated seller's total revenue, the number of observations is the number of simulated groups in each treatment  $\times$  20 rounds  $\times$  1,000 bootstraps.

No-Hint vs 1128.005 in HH-Hint ) but decrease when bidders face robot rivals (1126.575 in HR-No-Hint vs 1091.301 in HR-Hint ).

## 5 Discussion

In our study, providing subjects with a hint about SP through the advanced quiz increased the rate of dominant bidding from 25% in HH-No-Hint to 49% in HH-Hint. The degree of this effect is similar to that of providing advice, as reported in Masuda et al. (2022). Masuda et al. (2022) demonstrated that providing advice to subjects can increase the rate of dominant bidding from 20% to 47%. In their study, they assessed subjects' comprehension of Vickrey auction rules through a quiz similar to Basic Quiz in our study; however, their quiz did not measure or aim to enhance subjects' understanding of SP.

To investigate the effects of advice in our experimental environment, we designed two additional treatments. These two treatments follow the design of HH-Hint and HR-Hint, both of which include providing Hint Advanced Quiz to subjects and providing them with the same advice used in the study by Masuda et al. (2022).

Our results indicate that the Hint Advanced Quiz in our experiment has a similar effect size to the advice intervention studied by Masuda et al. (2022). The advice does not increase the rate of dominant bidding among subjects who got perfect scores, likely because they already understand the SP well. However, the advice is especially helpful for subjects with lower scores, who seem to have a weaker understanding of the SP. Details of the results are provided in the Online Appendix.

We classify bidders into two types —rational bidders and irrational bidders—based on their dominant bidding frequencies across all rounds. Rational bidders are defined as those with dominant bidding frequencies greater than or equal to 80%, while irrational bidders have dominant bidding frequencies below 20%.

We find that the SP hint converts a substantial proportion of irrational bidders into rational bidders. This conversion accounts for the increase in dominant bidding rates induced by the SP hint. In contrast, human interaction does not lead to such a clear conversion. Although human interaction has non-negligible effects on dominant bidding

rates, these effects are less robust than those of SP hints. Further details are provided in the Online Appendix.

## 6 Conclusion

In our experiment, we focused on two key factors that influence dominant bidding in homogeneous multi-unit Vickrey auctions: the subjects' understanding of SP and human interaction, which includes social preferences (spite and altruism), responses to strategic uncertainty, and tacit collusion. To analyze the effect of understanding SP, we compared the bidding behavior of subjects who took a quiz with SP hints and those who took a quiz without SP hints. To analyze the effect of human interaction, we compared the bidding behavior of subjects competing against robot rivals and those competing against human rivals. Our study demonstrates that a better understanding of SP is a crucial and strong driver of dominant bids. Conversely, although human interaction had a non-negligible impact, it did not have as much influence as the understanding of SP. This led us to conclude that the main factor causing dominated bidding was not human interaction but a lack of understanding of the concept of SP.

We raise several questions for future research. First, is the difficulty in understanding SP confined to Vickrey auctions, or is it a broader issue applicable to other types of auctions? As discussed in Section 1, several researchers have offered insights based on their experiments in which they aid subjects in recognizing SP. Recently, Gonczarowski et al. (2023) proposed menu descriptions of mechanisms to enable subjects to understand SP more easily. Second, what are the most effective ways to educate subjects about SP to encourage more dominant bidding?

In summary, our study contributes new insights to existing research on Vickrey auctions by focusing on the factors that lead to dominated bidding. Our findings highlight the importance of understanding SP as a key determinant of dominant bidding. This lays the groundwork for future research to delve deeper into the causes of dominated bidding and paves the way for targeted educational and design solutions that encourage more dominant bidding practices in auctions.

**Declaration of competing interest** The authors have no relevant or material financial interest that relates to the research described in the paper.

**Data availability** Data will be made available on request.

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# Online Appendix to “Toward an Understanding of Dominated Bidding in a Vickrey Auction Experiment”

Shigehiro Serizawa,\* Natsumi Shimada,† Tiffany Tsz Kwan Tse‡

June 11, 2026

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\*Faculty of Economics, Osaka University of Economics, Japan

†Graduate School of Economics and Management, Tohoku University, Japan

‡Corresponding author: Institute of Social and Economic Research, University of Osaka, Japan

## A Ratios of rational and irrational bidders

We categorize subjects into the following groups based on their dominant bidding frequencies  $x$ : “ $x = 0\%$ ”; “ $0\% < x < 20\%$ ”; “ $20\% \leq x < 40\%$ ”; “ $40\% \leq x < 60\%$ ”; “ $60\% \leq x < 80\%$ ”; “ $80\% \leq x < 100\%$ ”; “ $x = 100\%$ .” Each subject submits 40 bids (i.e., 20 rounds  $\times$  2 units per round). For instance, a subject who bids her true valuations 20 times is categorized as “ $40\% \leq x < 60\%$ .” Similarly, a subject who bids her true valuations 25 times is categorized as “ $60\% \leq x < 80\%$ .” Figure A1 shows the ratios of the subjects who bid their true valuations at various frequencies. Figure A1a shows the results for the overall dataset, whereas Figure A1b presents the outcomes for the data of subjects with perfect and imperfect scores in Advanced Quiz.

Figure A1 illustrates two distribution concentrations. One is the group of subjects whose dominant bidding frequencies are greater than or equal to 80%, and the other is the group of subjects whose dominant bidding frequencies are less than 20%. We call bidders in the first group “rational bidders” and those in the second group “irrational bidders.”<sup>1</sup> Subsequently, we employ a two-sample t-test to compare the ratios of rational and irrational bidders across the treatments.

### A.1 Rational bidders

First, we analyze the impact of SP hints on the ratios of rational bidders. Overall, our findings reveal that the ratios of rational bidders increases from 17% in HH-No-Hint to 36% in HH-Hint at the 5% significance level. The ratio increases from 21% in HR-No-Hint to 54% in HR-Hint at the 1% significance level. For subjects with perfect scores, the ratio increases from 17% in HH-No-Hint to 39% in HH-Hint at the 5% significance level and from 23% in HR-No-Hint to 68% in HR-Hint at the 1% significance level. Conversely, for subjects with imperfect scores in Advanced Quiz, the ratios of rational bidders remains similar between HH-No-Hint (14%) and HH-Hint (29%) with no significant difference ( $p = 0.494$ ). Similarly, there is no significant difference between HR-No-Hint (0%) and HR-Hint (9%) with respect to the ratios of rational bidders ( $p = 0.621$ ).

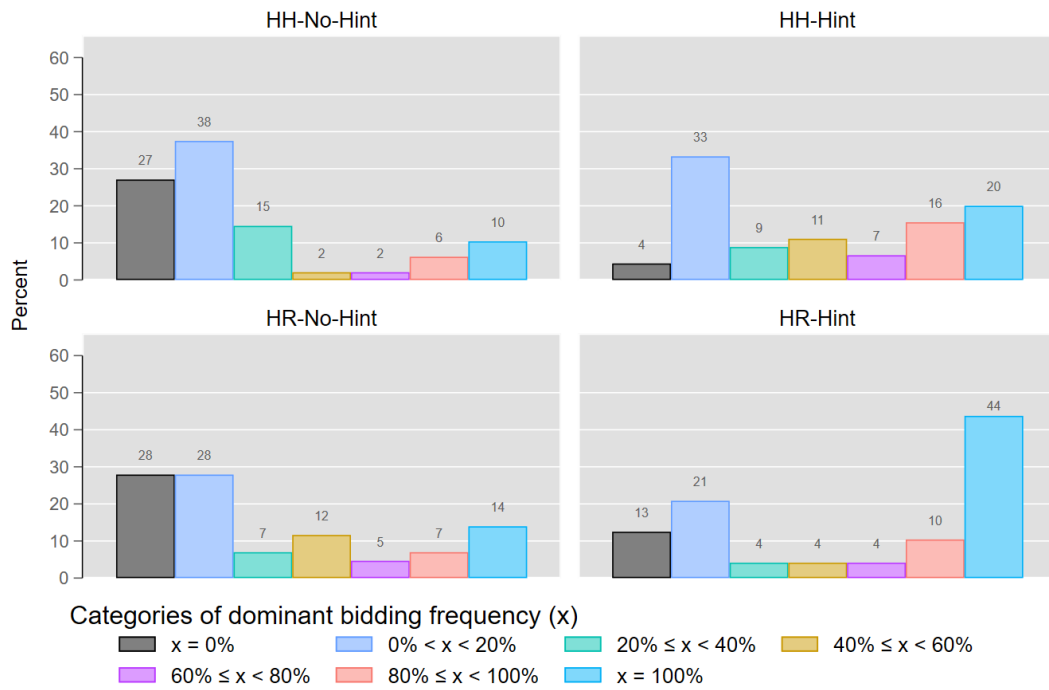
Second, we analyze the impact of human interaction on the ratios of rational bidders. For subjects given No-Hint Advanced Quiz, we observe no statistically significant difference in the ratios of rational bidders between HH-No-Hint and HR-No-Hint in the overall dataset (17% in HH-No-Hint vs 21% in HR-No-Hint,  $p = 0.607$ ), perfect score dataset (17% in HH-No-Hint vs 23% in HR-No-Hint,  $p = 0.546$ ), and imperfect score dataset (14% in HH-No-Hint vs 0% in HR-No-Hint,  $p = 0.545$ ). Nevertheless, when subjects are given Hint Advanced Quiz, we find a statistically significant increase in the ratios

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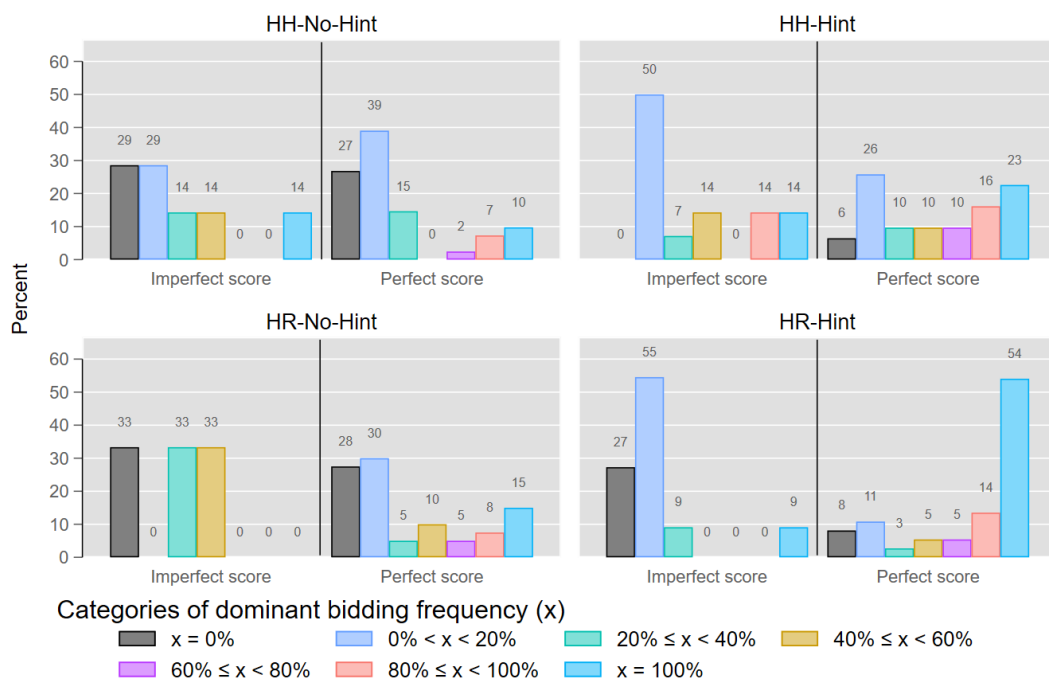
<sup>1</sup>We calculate the correlation between bidder types and Hint Advanced Quiz scores using the Spearman correlation method. We find a significant positive correlation between “rational bidders” and Hint Advanced Quiz scores ( $\rho = 0.305$ ,  $p < 0.01$ ) and a negative correlation between “irrational bidders” and Hint Advanced Quiz scores ( $\rho = -0.361$ ,  $p < 0.01$ ).

Figure A1: The ratios of rational and irrational bidders

(a) Overall



(b) Imperfect score vs Perfect score



of rational bidders, from 36% in HH-Hint to 54% in HR-Hint, at the 10% significance level. This increase is also pronounced among subjects with perfect scores in Advanced Quiz, with the ratio increasing significantly from 39% in HH-Hint to 68% in HR-Hint at the 5% significance level. Contrarily, no such increase is observed among subjects with imperfect scores in Advanced Quiz, with the ratio being 29% in HH-Hint and 9% in HR-Hint ( $p = 0.244$ ).

In summary, the SP hints exert a positive influence, particularly on subjects with perfect scores, compelling them to bid their true valuations frequently. A substantial ratio of these subjects comprises rational bidders when competing against robot rivals. Conversely, the effects of human interaction are mixed. We observe no significant impact on the ratios of rational bidders when subjects are given No-Hint Advanced Quiz but significant impacts when subjects receive Hint Advanced Quiz.

## A.2 Irrational bidders

First, we analyze the impact of SP hints on the ratios of irrational bidders. Overall, our findings reveal that the ratios of irrational bidders decrease from 65% in HH-No-Hint to 38% in HH-Hint at the 1% significance level. The ratios decrease from 56% in HR-No-Hint to 33% in HR-Hint at the 5% significance level. For subjects with perfect scores, the ratios decrease from 66% in HH-No-Hint to 32% in HH-Hint at the 1% significance level and from 58% in HR-No-Hint to 19% in HR-Hint at the 1% significance level. Conversely, for subjects with imperfect scores in Advanced Quiz, the ratios of irrational bidders remain similar between HH-No-Hint (57%) and HH-Hint (50%) with no significant difference ( $p = 0.772$ ) and also between HR-No-Hint (33%) and HR-Hint (82%) with no significant difference ( $p = 0.115$ ).

Second, we analyze the impact of human interaction on the ratios of irrational bidders. For subjects given No-Hint Advanced Quiz, we observe no statistically significant difference in the ratios of irrational bidders between HH-No-Hint and HR-No-Hint in the overall dataset (65% in HH-No-Hint vs 56% in HR-No-Hint,  $p = 0.399$ ), perfect score dataset (66% in HH-No-Hint vs 58% in HR-No-Hint,  $p = 0.446$ ), and imperfect score dataset (57% in HH-No-Hint vs 33% in HR-No-Hint,  $p = 0.545$ ). When subjects are given Hint Advanced Quiz, we find no statistically significant difference in the ratios of irrational bidders between HH-Hint and HR-Hint in the overall dataset (38% in HH-Hint vs 33% in HR-Hint,  $p = 0.659$ ), perfect score dataset (32% in HH-Hint vs 19% in HR-Hint,  $p = 0.211$ ), and imperfect score dataset (50% in HH-Hint vs 82% in HR-Hint,  $p = 0.108$ ).

In summary, the SP hint has a positive impact on reducing the ratio of irrational bidders. However, the factor of human interaction does not influence the ratios of irrational bidders, regardless of whether subjects are given Hint Advanced Quiz or No-Hint Advanced Quiz.

### **A.3 Converting irrational bidders to rational bidders**

The above results imply that SP hint converts a substantial ratio of irrational bidders into rational bidders. This conversion explains the increase of the dominant bidding rates caused by SP hint. Conversely, the above results imply that human interaction does not make such clear conversion. This differs from the results that human interaction has non-negligible effects on dominant bidding rates but is consistent with results that the impact of human interaction is not as robust as SP hints.

## B How did subjects bid in the auction, and why?

Based on Questions 5 and 6 of our post-experimental survey, we examine subjects’ bidding policies in the auction and the motivations for their policies. Question 5 is about the subjects’ bidding policies. It asks, “How did you bid in the auction?” subjects chose one of four answers:

- (a) Bid the amount of valuation
- (b) Bid higher than valuation
- (c) Bid lower than valuation
- (d) Other

Table B1: Survey of bidding policies (Question 5)

Treatments	HH-No-Hint	HH-Hint	HR-No-Hint	HR-Hint
Proportion of selection of choice (a)	27%	40%	35%	60%
Average dominant bid rates among subjects who select choice (a)	0.642	0.864	0.81	0.947
Proportion of selection of choice (b)	46%	51%	44%	27%
Average overbid rates among subjects who select choice (b)	0.814	0.682	0.754	0.808
Proportion of selection of choice (c)	4%	0%	5%	6%
Average underbid rates among subjects who select choice (c)	0.4		0.938	0.758
Proportion of selection of choice (d)	23%	9%	16%	6%
obs.	48	45	43	48

*Notes:* The number of observations is that of subjects in each treatment.

Table B1 summarizes the proportion of subjects selecting each answer in survey question 5 and their average dominant bid rates, overbid rates, and underbid rates. We report the correlation between “Choice (a) Bid the amount of valuation” and the average dominant bid rates using pairwise correlation analyses, specifically the Spearman correlation method. We find a significant correlation between “Choice (a)” and the average dominant bid rates obtained in the experiments ( $\rho = 0.793$ ,  $p < 0.01$ ). Additionally, using the Spearman correlation method, we find significant correlations between “Choice (b)” and the average overbid rates ( $\rho = 0.735$ ,  $p < 0.01$ ), as well as between “Choice (c)” and the average underbid rates ( $\rho = 0.302$ ,  $p < 0.01$ ). Therefore, we conclude that most subjects are likely to report their bidding policies honestly.

Question 6 concerns the motivations of subjects’ bidding policies. It asks subjects why they bid as they did in Question 5, and subjects choose one of four answers:

- (a) To maximize your earnings in the auction
- (b) To maximize your winning probability rather than to maximize your earnings in the auction
- (c) To make the earnings of other bidders smaller
- (d) To make the earnings of other bidders larger
- (e) Other

Choice (a) corresponds to the motivation assumed by standard auction theory. Choice (b) corresponds to the joy of winning (Cooper & Fang, 2008). Choices (c) and (d), respectively, correspond to social preferences of spite and altruism.

Table B2 summarizes the proportion of subjects selecting each choice in Question 6. The proportion of subjects selecting (a) was approximately half for each treatment. Moreover, the proportion of subjects who chose option (b) was approximately one-third for each treatment. These violations of the fundamental assumptions of auction theory may have caused dominated bidding. However, only a few subjects reported social preferences for spite and altruism. Thus, such social preferences may have had a limited impact on inducing dominated bidding.

Table B2: Survey of motivations of bidding policies (Question 6)

Treatments	HH-No-Hint	HH-Hint	HR-No-Hint	HR-Hint
Proportion of selection of choice (a)	48%	64%	58%	65%
Proportion of selection of choice (b)	33%	31%	28%	25%
Proportion of selection of choice (c)	2%	2%	5%	0%
Proportion of selection of choice (d)	0%	0%	0%	2%
Proportion of selection of choice (e)	17%	2%	9%	8%
obs.	48	45	43	48

We found that 21% of the subjects in HH-No-Hint, 38% in HH-Hint, 28% in HR-No-Hint, and 52% in HR-Hint chose (a) for Questions 5 and 6. These subjects understood that a dominant bidding strategy could maximize their earnings. The introduction of SP hints (Hint Advanced Quiz) led to an increase in the proportion of such subjects. This aligns with the results presented in Section 3. We also found that 29% of subjects in HH-No-Hint, 29% in HH-Hint, 26% in HR-No-Hint, and 19% in HR-Hint chose (b) for Questions 5 and 6. The objective of these subjects was to win the auction instead of maximizing payoffs, and indeed, they did so. Thus, these data reveal that the joy of

winning (Cooper & Fang, 2008) is also an important factor in dominated bidding. SP hints (Hint Advanced Quiz) did not decrease the proportion of such subjects.

Notably, 13% of the subjects in HH-No-Hint, 20% in HH-Hint, 16% in HR-No-Hint, and 6% in HR-Hint chose (b) for Question 5 and (a) for Question 6. These subjects assumed that overbidding could maximize their earnings—they failed to understand SP. The average scores for Advanced Quiz of these subjects were 10 in HH-No-Hint, 8.2 in HH-Hint, 10 in HR-No-Hint, and 8 in HR-Hint. The proportions of these subjects who got perfect scores in Advanced Quiz are 100% in HH-No-Hint, 56% in HH-Hint, 100% in HR-No-Hint, and 33% in HR-Hint. These data suggest that subjects who misunderstood SP and believed that overbidding could maximize their earnings tended to score low in Hint Advanced Quiz. Additionally, only a few subjects achieved a perfect score.

## C Advice effect

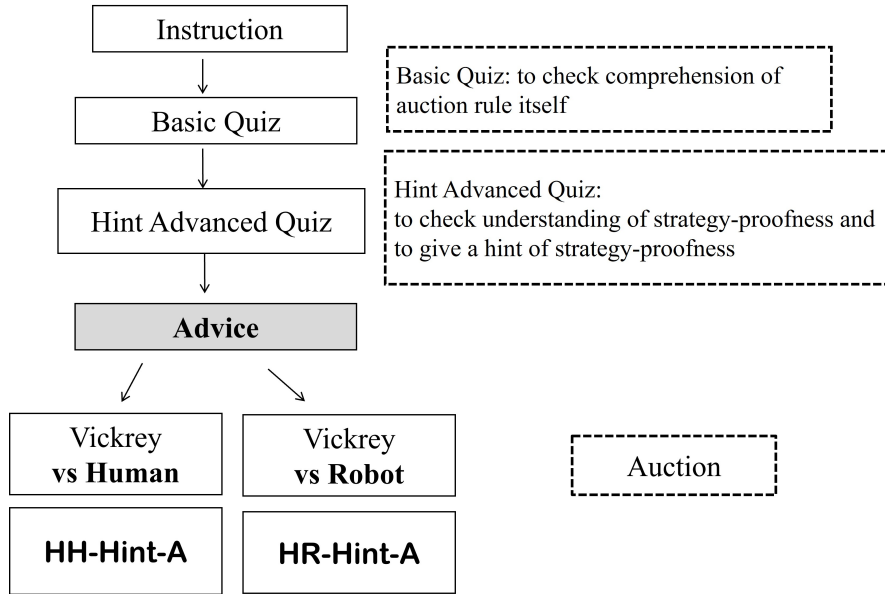
In our study, providing subjects with a hint about SP through the advanced quiz increased the rate of dominant bidding from 25% in HH-No-Hint to 49% in HH-Hint. The degree of this effect is similar to that of providing advice, as reported in Masuda et al. (2022). Masuda et al. (2022) demonstrated that providing advice to subjects can increase the rate of dominant bidding from 20% to 47%. In their study, they assessed subjects' comprehension of Vickrey auction rules through a quiz similar to Basic Quiz in our study; however, their quiz did not measure or aim to enhance subjects' understanding of SP.

To investigate the effects of advice in our experimental environment, we designed two additional treatments. These two treatments follow the design of HH-Hint and HR-Hint, both of which include providing Hint Advanced Quiz to subjects and providing them with the same advice used in the study by Masuda et al. (2022). Following Masuda et al. (2022), we did not inform subjects whether the advice was true or false, and instead instructed them to consider its validity on their own. We perform the following additional treatments:

- Treatment HH-Hint-A: only human subjects competed, and each subject was given Advanced Quiz with SP hints and advice
- Treatment HR-Hint-A: each subject competed with two robot rivals and was given Advanced Quiz with SP hints and advice

Figure C2 illustrates the flow of the experiments in HH-Hint-A and HR-Hint-A. The procedure for these experiments closely resembles that of HH-Hint and HR-Hint, with one exception. After the subjects completed Advanced Quiz with hints and listened to an audio explanation of the answer key, we distributed a paper containing the written advice. The text of the advice is as follows:

Figure C2: Flow of the experiment



The following advice is about the auction in which you are participating. Please consider carefully whether this advice is true or false. It is completely up to you whether you follow the advice or not.

*You can maximize your earnings by bidding your valuations as they are, regardless of what others bid.*

Subsequently, the subjects listened to an audio recording of this advice.

Table C1: Summary of treatments

Treatments	HH-Hint-A	HR-Hint-A
Type of Advanced Quiz	w/ hints	w/ hints
Nature of rivals	human	robot
No. of sessions	2	2
Duration (min)	150	150
No. of rounds	20	20
No. of subjects	42	40
Avg. payment (JPY)	5083	5089
Avg. score of Basic Quiz	9.310	9.725
Avg. score of Hint Advanced Quiz	8.786	9.650
No. of subjects with a perfect score in the Advanced Quiz	28	33

Table C1 summarizes the basic data for HH-Hint-A and HR-Hint-A. Table C2 shows the dominant bidding rates for HH-Hint, HR-Hint, HH-Hint-A, and HH-Hint-A. Using data from both units displayed in Panel (a), we examine whether the advice leads to higher rates of dominant bidding among subjects with a better understanding of

Table C2: Dominant bidding rates by treatment, Advanced Quiz scores, and unit

Treatments	(1) HH-Hint		(2) HH-Hint-A	(3) HR-Hint		(4) HR-Hint-A	(3) – (1)	(4) – (2)
(a) Both units								
All	0.489	<	0.576	0.617	<	0.748	0.128	0.172**
(S.E.)	(0.057)		(0.055)	(0.064)		(0.054)		
obs.	45		42	48		40		
Perfect score	0.522	<	0.567	0.751	<	0.798	0.230**	0.232***
(S.E.)	(0.069)		(0.065)	(0.064)		(0.056)		
obs.	31		28	37		33		
Imperfect score	0.418	<	0.595	0.166	<**	0.511	–0.252*	–0.084
(S.E.)	(0.104)		(0.107)	(0.090)		(0.135)		
obs.	14		14	11		7		
(b) Unit 1								
All	0.461	<	0.562	0.606	<*	0.759	0.145	0.197**
(S.E.)	(0.064)		(0.059)	(0.065)		(0.059)		
obs.	45		42	48		40		
Perfect score	0.508	<	0.555	0.736	<	0.808	0.228**	0.252***
(S.E.)	(0.080)		(0.072)	(0.067)		(0.061)		
obs.	31		28	37		33		
Imperfect score	0.357	<	0.575	0.168	<**	0.529	–0.189	–0.046
(S.E.)	(0.104)		(0.108)	(0.089)		(0.156)		
obs.	14		14	11		7		
(c) Unit 2								
All	0.518	<	0.59	0.628	<	0.738	0.110	0.147*
(S.E.)	(0.058)		(0.057)	(0.065)		(0.052)		
obs.	45		42	48		40		
Perfect score	0.535	<	0.579	0.766	<	0.789	0.231**	0.211**
(S.E.)	(0.069)		(0.067)	(0.065)		(0.053)		
obs.	31		28	37		33		
Imperfect score	0.479	<	0.614	0.164	<**	0.493	–0.315**	–0.121
(S.E.)	(0.110)		(0.110)	(0.091)		(0.131)		
obs.	14		14	11		7		

Notes: a) We compare the dominant bidding rates between treatments by using two-sample t-tests. b) \* \*\* and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. c) Numbers in parentheses are standard errors. d) The unit of observations is the subject. The total number of observations is the number of subjects in each treatment.

SP. Specifically, we use two-sample t-tests to compare the rates of dominant bidding between HH-Hint and HH-Hint-A when rivals are human and between HR-Hint and HR-Hint-A when rivals are robots.

Overall, our findings indicate that providing advice increases the rate of dominant bidding, although the effect in our experiment is not statistically significant and is smaller than that reported in Masuda et al. (2022). The mean increase from HH-Hint to HH-Hint-A is 8.675% ( $p = 0.281$ ), and that from HR-Hint to HR-Hint-A is 13.094% ( $p = 0.129$ ). As mentioned in Online Appendix A, approximately one-third of subjects reported that they overbid to increase their winning probabilities rather than their earnings. Therefore, there is a limit to increasing dominant bidding through understanding SP. We hypothesize that this limit made the effect of advice in our experiment less effective than that in Masuda et al. (2022) because the dominant bidding rates in HH-Hint and HR-Hint were already high and had less potential for further improvement.

This advice has been demonstrated to be highly effective when we focus on data pertaining to subjects who do not achieve perfect scores in Hint Advanced Quiz. For subjects with imperfect scores in Hint Advanced Quiz, the mean increases from HH-Hint to HH-Hint-A are 17.679% ( $p = 0.247$ ), and those from HR-Hint to HR-Hint-A are 34.481% ( $p = 0.042$ ). For subjects with perfect scores in Hint Advanced Quiz, the mean increase from HH-Hint to HH-Hint-A is 4.519% ( $p = 0.638$ ). The mean increase from HR-Hint to HR-Hint-A is 4.713% ( $p = 0.583$ ). This outcome aligns with our hypothesis, suggesting that subjects with imperfect scores had lower initial dominant bidding rates and more potential for improvement.

Similar to the comparison between HH-Hint and HR-Hint, removing human interaction leads to an increased rate of dominant bidding from HH-Hint-A to HR-Hint-A. However, this increase is observed only among subjects who achieved perfect scores on the Hint Advanced Quiz; no such effect is found among those with imperfect scores.

Our results indicate that the Hint Advanced Quiz in our experiment has a similar effect size to the advice intervention studied by Masuda et al. (2022). The advice does not increase the rate of dominant bidding among subjects who got perfect scores, likely because they already understand the SP well. However, the advice is especially helpful for subjects with lower scores, who seem to have a weaker understanding of the SP.

## D Cognitive ability, risk aversion, and loss aversion

Understanding SP may be related to subjects' cognitive abilities. We examine the correlation between subjects' cognitive abilities and their quiz scores. Approximately half of the subjects participated in an experiment conducted by Hanaki et al. (2022). From their dataset, we obtained data on the subjects' cognitive abilities, risk aversion, and loss aversion.

For cognitive ability, we used the subjects' International Cognitive Ability Resource (ICAR) scores, as proposed by Condon and Revelle (2014)<sup>2</sup>. Hanaki et al. (2022) used a three-dimensional (3D) rotation measure (four questions) and a matrix reasoning measure (four questions) from those included in ICAR-16 (Condon and Revelle 2014, Table 4). Subjects were given 40 seconds to answer each of the 3D rotation questions and 30 seconds to answer each matrix reasoning question. The maximum possible score was 8, and the subjects correctly answered an average of 2–3 questions.

For risk aversion, we collected the subjects' risk attitudes from Hanaki et al. (2022)'s experiments, in which they used the designs of Noussair et al. (2014) and Masuda and Lee (2019). The elicitation task comprised five questions related to risk aversion. For each question, subjects were asked to choose between two lotteries. The measure of risk aversion is the number of safe options that a subject chooses from five questions. The maximum score was 5, and the subjects selected an average of three safe options.

For loss aversion, Hanaki et al. (2022) used the experimental task proposed by Köbberling and Wakker (2005) to measure the degree of loss aversion. They asked subjects to choose between a sure zero payment and a lottery in which they would get 600 JPY with a 50% chance or lose X JPY with a 50% chance, where  $X = 120, 240, 360, 480, 600, \text{ or } 720$ . They assumed that loss-averse individuals tend to choose a sure zero-payment option. Loss aversion was measured as the number of safe options in the six questions. The maximum score was 6, and the subjects selected an average of three safe options.

We report the correlations between ICAR and quiz scores using pairwise correlation analyses, specifically the Spearman correlation method. We found no correlation between ICAR scores and Basic Quiz scores ( $\rho = 0.085, p = 0.399$ ) or between ICAR scores and Advanced Quiz scores w/o hints ( $\rho = -0.024, p = 0.864$ ). However, we found a significant correlation between ICAR and Hint Advanced Quiz scores ( $\rho = 0.373, p < 0.01$ ). We conclude that achieving a perfect score in Hint Advanced Quiz requires cognitive ability. Thus, understanding SP also appears to require cognitive abilities.

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<sup>2</sup>See the ICAR team website, <https://icar-project.com>, for further details.

Table D1: Demographic data

Treatments	HH-No-Hint	HH-Hint	HR-No-Hint	HR-Hint
(i) Cognitive ability (ICAR scores)	2.129	2.318	3.143	2.815
obs.	31	22	21	27
(ii) Risk aversion (Noussair et al., 2014)	3.323	3.182	3.217	3.586
obs.	31	22	23	29
(iii) Loss aversion (Köbberling & Wakker, 2005)	3.226	2.727	2.381	3.852
obs.	31	22	21	27
Total number of subjects	48	45	43	48

Table D2: Regression analysis of treatment dummy on dominant bidding by controlling preferences

	Both (1)	Unit 1 (2)	Unit 2 (3)
SP hint	1.279*** (0.488)	1.036** (0.528)	1.528*** (0.495)
Robot	0.159 (0.524)	-0.284 (0.590)	0.534 (0.551)
SP hint $\times$ Robot	-0.045 (0.741)	0.622 (0.820)	-0.647 (0.767)
Cognitive ability	0.147 (0.125)	0.167 (0.133)	0.130 (0.124)
Risk aversion	0.030 (0.140)	0.0452 (0.146)	0.0143 (0.145)
Loss aversion	-0.130 (0.118)	-0.136 (0.126)	-0.125 (0.122)
Constant	-1.177* (0.699)	-1.280* (0.727)	-1.076 (0.698)
Observations	3,920	1,960	1,960
Clusters	98	98	98
Wald Chi2	13.81	12.61	14.34
Prob >Chi2	0.032	0.050	0.026

*Notes:* a) We conducted logit regression of the dominant bidding dummy on the SP hint dummy and robot dummy conditional on cognitive ability, risk aversion, and loss aversion with robust standard error clustered at the individual level. b) Dominant bidding dummy equals 1 if subjects submitted a dominant bid in a period and 0 otherwise. SP hint dummy equals 1 if subjects take Hint Advanced Quiz and 0 if they take No-Hint Advanced Quiz. Robot dummy equals 1 if subjects compete against robot rivals and 0 if they compete against human rivals. Cognitive ability ranges from 0 to 8, risk aversion ranges from 0 to 5, and loss aversion ranges from 0 to 6. c) \* \*\* and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. d) Numbers in parentheses are standard errors. e) The total number of observations is the number of subjects  $\times$  number of periods  $\times$  number of units in each treatment.

Some may argue that factors other than understanding SP, such as subjects' preferences, could affect bidding behavior. To address this, we run the regression presented in Table 4 of the main paper, which additionally controls for subjects' cognitive ability levels, risk aversion, and loss aversion. Table D2 presents these results. These results confirm our original findings—the SP hint dummy has a statistically significant positive impact on dominant bidding. This suggests that providing SP hints in Hint Advanced Quiz promotes dominant bidding, even after controlling for cognitive ability, risk aversion levels, and loss aversion levels.

## **E Experimental instructions and quizzes**

This section contains experimental materials. The materials are originally in Japanese and translated to English. From next page, subsection titles and page numbers are now in the header of each page.

D.1 HH-No-Hint and HH-Hint (competing against human rivals)

D.2 HR-No-Hint and HR-Hint (competing against robot rivals)

D.3 Basic Quiz

D.4 Hint Advanced Quiz

D.5 No-Hint Advanced Quiz

## Instructions

**Notice:**

- Please follow the instructions of the experimenter, but do not operate PC otherwise.
- Please do not communicate or exchange memos with other subjects.
- Please do not watch the behaviors and screens of other subjects.
- Please turn off your mobile phone and put it into your bag.
- Please raise your hand when you have a question.
- You can take a memo using the pen on your desk. You can also use the calculator on your desk.

**Overview of experiment**

- Today’s Experiment is a sequence of auctions. In an auction, subjects bid for items that they wish, and subjects with the highest bids win the items. Subjects’ bids also determine the winners’ payment. Hereafter, a subject bidding for items is called a “bidder.”
- In this experiment, auctions are conducted for 20 rounds, and three bidders participate in each auction. You play the role of one of the three bidders, and the other two bidders are other subjects. You will be randomly matched with the other two subjects in each round of auction. You will not know who you are matched with either during or after the experiment.
- Your reward after the experiment is based on the results of 20 rounds of auction in which you participate.

**Procedure of experiment**

- (1) Two units of an identical object are auctioned off in every period. Three bidders, including yourself, participate in each round of the auction.
- (2) If a bidder wins an item, they will draw satisfaction from the item. Such satisfaction is assumed to be measured by money, and the satisfaction as measured by money is called “valuation.” The satisfaction from the first unit is called *the valuation of the first unit*, and that from the second unit is called *the valuation of the second unit*.
- (3) In this experiment, your valuations in each round of auction are chosen by PC. In each round, PC randomly draws two values from the interval 10 JPY to 1,000 JPY in increments of 10 JPY. The higher value is your valuation of the first unit, and the lower one is your valuation of the second unit. This assumes that your satisfaction with the second unit is less than that obtained from the first.

The valuations of the other subjects are determined similarly in each round. Thus, different subjects have different valuations. However, in each round, the valuation of each bidder from the second unit is lower than that of the first unit. The other bidders will not know your valuations, and you will not know others’ valuations.

(4) In this experiment, you are required to submit your “bid for the first unit” and “bid for the second unit” to the experimenter. Please note the following three points:

- Your “bid for the first unit” must exceed your “bid for the second unit.”
- Your bids must be at least 0 JPY.
- Your bids must be in increments of 10 JPY.

(5) In this experiment, each of the three bidders submit two bids. Thus, there is a total of six bids. The two highest bids are winning bids, and a bidder who submits the winning bid(s) wins the corresponding object(s). In the scenario of a tie among the highest bids, the program selects the winning bids with equal probabilities. This procedure determines the number of units won by each bidder.

(6) How to determine the payments of winning bidders is explained later. The *earnings* of a winning bidder is the sum of the valuations of the units they win minus their payment. The *earnings* of a non-winning bidder is zero.

#### Calculation of payments and earnings

We explain how to calculate a bidder’s payments and earnings using numerical examples. There are three bidders: A, B, and C. Here, we focus on bidder A. In the following examples, amounts displayed are in JPY.

**(1) In the scenario where a bidder wins one unit:** A bidder who wins one unit pays the highest bid among the other bidders’ losing bids.

EXAMPLE 1. Suppose A’s valuations for the first and second units are 680 and 480, respectively. The table below shows the bids from the three bidders.

Bidder	Bid for the first unit	Bid for the second unit
A	500	450
B	600	300
C	400	250

The winning bids are “A’s 500” and “B’s 600.” The losing bids are “A’s 450,” “B’s 300,” “C’s 400,” and “C’s 250.” Thus, for bidder A, the other bidders’ losing bids are “B’s 300,” “C’s 400,” and “C’s 250.” Bidder A pays the highest bid among these losing bids—400. This payment differs from A’s bid for the first unit. Bidder A earns the following amount:

$$680 \text{ (valuation for the first unit)} - 400 \text{ (payment)} = 280$$

EXAMPLE 2. Suppose A’s values for the first and second units are 680 and 480, respectively. The table below displays the bids from the three bidders.

Bidder	Bid for the first unit	Bid for the second unit
A	800	350
B	750	300
C	700	250

The winning bids are “A’s 800” and “B’s 750.” Thus, bidder A wins one unit. The losing bids are “A’s 350,” “B’s 300,” “C’s 700,” and “C’s 250.” Thus, for bidder A, the other bidders’ losing bids are “B’s 300,” “C’s 700,” and “C’s 250.” Bidder A pays the highest bid among these losing bids—700. Note that this payment differs from A’s bid for the first unit. Subsequently, bidder A earns the following amount:

$$680 \text{ (valuation for the first unit)} - 700 \text{ (payment)} = -20$$

**(2) In the scenario where a bidder wins two units:** A bidder who wins two units pays the sum of the highest and second-highest bids from among the losing bids.

EXAMPLE 3. Suppose A’s values for the first and second units are 680 and 480, respectively. The table below displays the bids from the three bidders.

Bidder	Bid for the first unit	Bid for the second unit
A	600	550
B	500	300
C	400	250

The winning bids are “A’s 600” and “A’s 550.” The losing bids are “B’s 500,” “B’s 300,” “C’s 400,” and “C’s 250.” Bidder A pays the sum of the highest and second-highest bids among the losing bids— $400 + 500 = 900$ . This payment differs from that in A’s bids. Subsequently, bidder A earns the following amount:

$$680 \text{ (valuation for the first unit)} + 480 \text{ (valuation for the second unit)} - 900 \text{ (payment)} = 260$$

EXAMPLE 4. Suppose A's values for the first and second units are 680 and 480, respectively. The bids of the three bidders are as follows:

Bidder	Bid for the first unit	Bid for the second unit
A	900	850
B	800	600
C	700	550

The winning bids are A's 900 and A's 850. The losing bids are "B's 800," "B's 600," "C's 700," and "C's 550." Thus, bidder A pays 1,500, the sum of the highest bid of 800 and the second highest bid of 700 from the losing bids. A's payment differs from A's bids. A's earnings are calculated as follows:

$$680 \text{ (valuation for the first unit)} + 480 \text{ (valuation for the second unit)} - 1500 \text{ (payment)} = -340$$

The earnings calculation method is summarized as follows:

- In the scenario where you win one unit, and the third highest bid is yours:

$$\text{Your earnings} = \text{your valuation for the first unit} - \text{fourth highest bid}$$

- In the scenario where you win one unit, and the third highest bid is not yours:

$$\text{Your earnings} = \text{your valuation for the first unit} - \text{third highest bid}$$

Note that when the payment is higher than the value of the first unit, your earnings are negative.

- In the scenario where you win two units:

$$\begin{aligned} \text{Your earnings} &= (\text{your valuation for first unit} + \text{your valuation for second unit}) \\ &\quad - (\text{third highest bid} + \text{fourth highest bid}) \end{aligned}$$

Note that when your payment is higher than the sum of your values of the first and second units, your earnings will be negative.

- If you do not win anything, your earnings are 0.

Rewards.

- We pay the sum of your earnings over all 20-round auctions as a reward.
- Before the auctions, you will answer Quizzes 1 and 2. Each quiz comprises ten questions. In addition to the earnings from auctions, you will be paid according to your scores in Quizzes 1 and 2.
- The total reward is the sum of your earnings from auctions and rewards based on quiz scores.

## Instructions

### Notice:

- Please follow the instructions of the experimenter, but do not operate PC otherwise.
- Please do not communicate or exchange memos with other subjects.
- Please do not watch the behaviors and screens of other subjects.
- Please turn off your mobile phone and put it into your bag.
- Please raise your hand when you have a question.
- You can take a memo using the pen on your desk. You can also use the calculator on your desk.

### Overview of experiment

- Today’s Experiment is a sequence of auctions. In an auction, subjects bid for items that they wish, and subjects with the highest bids win the items. Subjects’ bids also determine the winners’ payment. Hereafter, a subject bidding for items is called a “bidder.”
- In this experiment, auctions are conducted for 20 rounds, and three bidders participate in each auction. You play the role of one of the three bidders, and the other two bidders are played by PC.
- Your reward after the experiment is based on the results of 20 rounds of auction in which you participate.

### Procedure of experiment

- (1) Two units of an identical object will be auctioned off in every period. Three bidders, including yourself, participate in each round of the auction. However, bidders other than you are robots.
- (2) If a bidder wins an item, they will draw satisfaction from the item. Such satisfaction is assumed to be measured by money, and satisfaction as measured by money is called “valuation.” The satisfaction from the first unit is called *the valuation from the first unit*, and that from the second unit is called *the valuation of the second unit*.
- (3) In this experiment, your valuations in each round of auction is chosen by PC. In each round, PC randomly draws two values from the interval from 10 JPY to 1,000 JPY in increments of 10 JPY. The higher value is your valuation from the first unit, and the lower one is your valuation from the second unit. This assumes that your satisfaction with the second unit is less than that with the first.
- (4) In this experiment, you will submit your “bids for the first ” and “second units” to the experimenter. Please note the following three points:
  - Your “bid for the first unit” must exceed your “bid for the second unit.”
  - Your bids must be at least 0 JPY.
  - Your bids must be in increments of 10 JPY.

(5) As a bidder, a robot will randomly draw two values from the interval 10 JPY to 1,000 JPY with increments of 10 JPY. The higher value is the bid for the first unit of the robot as a bidder, and the lower one is the bid for the second unit. The bids of the other bidder (also a robot) are determined similarly.

(6) In this experiment, you are required to submit two bids, and the other two bidders (played by robots) also submit two bids. Thus, there will be a total of six bids. The two highest bids are winning bids, and a bidder who submits the winning bid(s) wins the corresponding object(s). In case of a tie among the highest bids, the program selects the winning bids with equal probabilities. This procedure determines the number of units won by each bidder.

(7) How to determine the payments of winning bidders is explained later. The *earnings* of a winning bidder is the sum of the valuations of the units that they win minus their payment. The *earnings* of a non-winning bidder is zero.

### Calculation of payments and earnings

We explain how to calculate a bidder's payments and earnings using numerical examples. There are three bidders: A, B, and C. Here, we focus on bidder A. In the following examples, amounts displayed are in JPY.

**(1) In the scenario where a bidder wins one unit:** A bidder who wins one unit pays the highest bid among the other bidders' losing bids.

EXAMPLE 1. Suppose A's valuations for the first and second units are 680 and 480, respectively. The table below shows the bids from the three bidders.

Bidder	Bid for the first unit	Bid for the second unit
A	500	450
B	600	300
C	400	250

The winning bids are "A's 500" and "B's 600." The losing bids are "A's 450," "B's 300," "C's 400," and "C's 250." Thus, for bidder A, the other bidders' losing bids are "B's 300," "C's 400," and "C's 250." Bidder A pays the highest bid among these losing bids—400. This payment differs from A's bid for the first unit. Bidder A earns the following amount:

$$680 \text{ (valuation for the first unit)} - 400 \text{ (payment)} = 280$$

EXAMPLE 2. Suppose A’s values for the first and second units are 680 and 480, respectively. The table below displays the bids from the three bidders.

Bidder	Bid for the first unit	Bid for the second unit
A	800	350
B	750	300
C	700	250

The winning bids are “A’s 800” and “B’s 750.” Thus, bidder A wins one unit. The losing bids are “A’s 350,” “B’s 300,” “C’s 700,” and “C’s 250.” Thus, for bidder A, the other bidders’ losing bids are “B’s 300,” “C’s 700,” and “C’s 250.” Bidder A pays the highest bid among these losing bids—700. Note that this payment differs from A’s bid for the first unit. Subsequently, bidder A earns the following amount:

$$680 \text{ (valuation for the first unit)} - 700 \text{ (payment)} = -20$$

**(2) In the scenario where a bidder wins two units:** A bidder who wins two units pays the sum of the highest and second-highest bids from among the other bidders’ losing bids.

EXAMPLE 3. Suppose A’s values for the first and second units are 680 and 480, respectively. The table below displays the bids from the three bidders.

Bidder	Bid for the first unit	Bid for the second unit
A	600	550
B	500	300
C	400	250

The winning bids are “A’s 600” and “A’s 550.” The losing bids are “B’s 500,” “B’s 300,” “C’s 400,” and “C’s 250.” Bidder A pays the sum of the highest and second-highest bids among the losing bids— $400 + 500 = 900$ . This payment differs from A’s bids. Subsequently, bidder A earns the following amount:

$$680 \text{ (valuation for the first unit)} + 480 \text{ (valuation for the second unit)} - 900 \text{ (payment)} = 260$$

EXAMPLE 4. Suppose A's values for the first and second units are 680 and 480, respectively. The bids of the three bidders are as follows:

Bidder	Bid for the first unit	Bid for the second unit
A	900	850
B	800	600
C	700	550

The winning bids are A's 900 and A's 850. The losing bids are "B's 800," "B's 600," "C's 700," and "C's 550." Thus, bidder A pays 1,500, the sum of the highest bid of 800 and the second highest bid of 700 from the losing bids. A's payment differs from A's bids. A's earnings are calculated as follows:

$$680 \text{ (valuation for the first unit)} + 480 \text{ (valuation for the second unit)} - 1500 \text{ (payment)} = -340$$

The earnings calculation method is summarized as follows:

- In the scenario where you win one unit, and the the third highest bid is yours:

$$\text{Your earnings} = \text{your valuation for the first unit} - \text{fourth highest bid}$$

- In the scenario where you win one unit, and the third-highest bid is not yours:

$$\text{Your earnings} = \text{your valuation for the first unit} - \text{third highest bid}$$

Note that when your payment is higher than your value for the first unit, your earnings will be negative.

- In the scenario where you win two units:

$$\begin{aligned} \text{Your earnings} &= (\text{your valuation for first unit} + \text{your valuation for second unit}) \\ &\quad - (\text{third highest bid} + \text{fourth highest bid}) \end{aligned}$$

Note that when your payment is higher than the sum of your values for the first and second units, your earnings will be negative.

- If you do not win anything, your earnings are 0.

#### Rewards

- We pay the sum of your earnings over all 20-round auctions as a reward.
- Before the auctions, you will answer Quizzes 1 and 2. Each quiz comprises ten questions. In addition to the earnings from auctions, you will be paid according to your scores from Quizzes 1 and 2.
- The total reward is the sum of your earnings from auctions and rewards based on quiz scores.

## Basic Quiz

Seat number \_\_\_\_\_

Please answer all the following questions. You will earn 100 JPY for each correct answer. Please refer to the instructions if necessary.

Assume that the bids from the three bidders and bidder A's valuations are as given in the table below. Please answer Questions 1–4 based on the table.

	First unit	Second unit
Bidder A's bid	800	500
Bidder B's bid	1000	700
Bidder C's bid	600	500
Bidder A's valuation	900	700

[Question 1] (Two) Winning bids Answer: \_\_\_\_\_

[Question 2] Bidder A's payment Answer: \_\_\_\_\_

[Question 3] Bidder A's earning (Their valuations on the items they win – Payment)  
Answer: \_\_\_\_\_

[Question 4] Bidder C's payment Answer: \_\_\_\_\_

Assume that the bids of the three bidders and bidder B's valuations are as given in the table below. Please answer Questions 5–7 based on the table.

	First unit	Second unit
Bidder A's bid	650	500
Bidder B's bid	1000	700
Bidder C's bid	600	500
Bidder B's valuation	950	800

[Question 5] (Two) Winning bids Answer: \_\_\_\_\_

[Question 6] Bidder B's payment Answer: \_\_\_\_\_

[Question 7] Bidder B's earning (Their valuations on the items they win – Payment)  
Answer: \_\_\_\_\_.

Assume that the bids of the three bidders and bidder C's valuations are as given in the table below. Please answer Questions 8–10 based on the table.

	First unit	Second unit
Bidder A's bid	800	500
Bidder B's bid	1000	700
Bidder C's bid	900	500
Bidder B's valuation	500	400

[Question 8] (Two) Winning bids Answer: \_\_\_\_\_

[Question 9] Bidder B's payment Answer: \_\_\_\_\_

[Question 10] Bidder B's earning (Their valuations on the items they win – Payment)  
Answer: \_\_\_\_\_

## Advanced Quiz

Please answer all the following questions. You will earn 100 JPY for each correct answer. Please refer to the instructions if necessary.

Assume that you are bidder B, and your valuations of the first and second units are 700 and 400, respectively. Maintain these assumptions for Questions 1–10 below. For each question, select the correct answers from the choices provided in the table below, where the the first and second figures in each choice are the bids of the first and second units, respectively. If several choices are correct, select all of them.

Choice a: (900, 820)	Choice b: (780, 500)	Choice c: (700, 400)
Choice d: (400, 390)	Choice e: (310, 200)	Choice f: (660, 200)

The calculation sheets for these questions are attached on pages 4–6. Use them if necessary. (However, the calculation sheets will not be marked.)

In Questions 1 and 2, assume that you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the two questions is shown on page 4.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	380	300
C	300	250

[Question 1] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 2] Select the choices that maximize your earnings (the sum of valuations of the units you win – your payments). (Note that if the earnings from all choices are nonpositive, the maximized earnings may be zero.)

Answer: \_\_\_\_\_

Seat number \_\_\_\_\_

In Questions 3–6, assume that you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 5.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	650	300
C	750	450

[Question 3] Select the choices that make your earnings (the sum of valuations of the units you win – your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 4] Select the choices that make your earnings (the sum of valuations of the units you win – your payments) negative. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 5] Select the choices that maximize your earnings (the sum of valuations of the units you win – your payments). (Note that if the earnings from all choices are nonpositive, the maximized earnings may be zero.)

Answer: \_\_\_\_\_

[Question 6] Select the choices that are the correct answers of both Questions 2 and 5—the choices that maximize your earnings for both of the two expectations about the bids of the two other bidders. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

Seat number \_\_\_\_\_

In Questions 7–9, assume that you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 6.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	800	660
C	750	500

[Question 7] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 8] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) negative. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 9] Select the choices that maximize your earnings (the sum of valuations of the units you win - your payments). (Note that if the earnings from all choices are nonpositive, the maximized earnings may be zero.)

Answer: \_\_\_\_\_

[Question 10] Select the choices that are the common answers of all of Questions 2, 5, and 9—the choices that maximize your earnings for all of the three expectations about the bids of the two other bidders. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

## Calculation sheets for Questions 1 and 2

	Bid for 1st unit	Bid for 2nd unit
Bidder A	380	300
Bidder C	300	250
Choice a	900	820
Choice b	780	500
Choice c	700	400
Choice d	400	390
Choice e	310	200
Choice f	660	200
Your valuation	700	400

Computation for Choice a: (900, 820)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice b: (780, 500)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice c: (700, 400)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice d: (400, 390)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice e: (310, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice f: (660, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Calculation sheets for Questions 3–6

	Bid for 1st unit	Bid for 2nd unit
Bidder A	650	300
Bidder C	750	450
Choice a	900	820
Choice b	780	500
Choice c	700	400
Choice d	400	390
Choice e	310	200
Choice f	660	200
Your valuation	700	400

Computation for Choice a: (900, 820)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice b: (780, 500)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice c: (700, 400)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice d: (400, 390)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice e: (310, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice f: (660, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Calculation sheets for Questions 7–9

	Bid for 1st unit	Bid for 2nd unit
Bidder A	800	660
Bidder C	750	500
Choice a	900	820
Choice b	780	500
Choice c	700	400
Choice d	400	390
Choice e	310	200
Choice f	660	200
Your valuation	700	400

Computation for Choice a: (900, 820)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice b: (780, 500)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice c: (700, 400)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice d: (400, 390)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice e: (310, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice f: (660, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Seat number \_\_\_\_\_

## Advanced Quiz

Please answer all the following questions. You will earn 100 JPY for each correct answer. Please refer to the instructions if necessary.

Assume that you are Bidder B in Questions 1–10. For each question, select the correct answers from the choices given in the table below, where the first and second figures in each choice are the bids of the first and second units, respectively. If several choices are correct, select all of them.

Choice a: (900, 820)	Choice b: (780, 500)	Choice c: (700, 400)
Choice d: (400, 390)	Choice e: (310, 200)	Choice f: (660, 200)

The calculation sheets for these questions are attached on pages 4–6. Use them if necessary. (However, the calculation sheets are not marked.)

In Questions 1–3, assume that your valuations of the first and second units are 500 and 300, respectively, and you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 4.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	380	300
C	300	250

[Question 1] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 2] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) negative. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 3] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) positive. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

Seat number \_\_\_\_\_

In Questions 4–6, assume that your valuations of the first and second units are 710 and 290, respectively, and you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 5.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	650	300
C	750	450

[Question 4] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 5] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) negative. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 6] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) positive. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

Seat number \_\_\_\_\_

In Questions 7–9, assume that your valuations of the first and second units are 730 and 370, respectively, and you expect the other two bidders (A and C) to bid as shown in the table below. The calculation sheet for the three questions is shown on page 6.

Bidder	Bid for 1st unit	Bid for 2nd unit
A	800	660
C	750	500

[Question 7] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) zero. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 8] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) negative. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 9] Select the choices that make your earnings (the sum of valuations of the units you win - your payments) positive. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

[Question 10] Select the choices that are the common answers of all of Questions 1, 4, and 7—the choices that make your earnings zero for all of the three expectations about the bids of the two other bidders. If no such choice exists, answer “none.”

Answer: \_\_\_\_\_

Seat number \_\_\_\_\_

## Calculation sheets for Questions 1 and 2

	Bid for 1st unit	Bid for 2nd unit
Bidder A	380	300
Bidder C	300	250
Choice a	900	820
Choice b	780	500
Choice c	700	400
Choice d	400	390
Choice e	310	200
Choice f	660	200
Your valuation	500	300

Computation for Choice a: (900, 820)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice b: (780, 500)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice c: (700, 400)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice d: (400, 390)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice e: (310, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice f: (660, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Seat number \_\_\_\_\_

Calculation sheets for Questions 4–6

	Bid for 1st unit	Bid for 2nd unit
Bidder A	650	300
Bidder C	750	450
Choice a	900	820
Choice b	780	500
Choice c	700	400
Choice d	400	390
Choice e	310	200
Choice f	660	200
Your valuation	710	290

Computation for Choice a: (900, 820)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice b: (780, 500)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice c: (700, 400)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice d: (400, 390)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice e: (310, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice f: (660, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Seat number \_\_\_\_\_

Calculation sheets for Questions 7–9

	Bid for 1st unit	Bid for 2nd unit
Bidder A	800	660
Bidder C	750	500
Choice a	900	820
Choice b	780	500
Choice c	700	400
Choice d	400	390
Choice e	310	200
Choice f	660	200
Your valuation	730	370

Computation for Choice a: (900, 820)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice b: (780, 500)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice c: (700, 400)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice d: (400, 390)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice e: (310, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

Computation for Choice f: (660, 200)

Units you win	Sum of valuations of units you win	Payment	Earning

## F Post-experiment survey

1. Please indicate your seat number for today's experiment. \_\_\_\_\_
2. Please select your gender.  Female  Male  Do not answer
3. Please select your major. \_\_\_\_\_
4. Did you understand the rules of today's auction before it started?
  - Very well
  - Well
  - Not so much
  - Little
5. How did you bid in the auction?
  - Bid the amount of valuation
  - Bid higher than valuation
  - Bid lower than valuation
  - Other: \_\_\_\_\_
6. Select the reason for bidding as you did in 5) from the choices below.
  - To maximize your earnings in the auction.
  - To maximize your winning probability rather than to maximize your earnings in the auction.
  - To make the earnings of other bidders smaller.
  - To make the earnings of other bidders larger.
  - Other: \_\_\_\_\_

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