Does Jump-bidding Increase Sellers' Revenue? Theory and Experiment*

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Abstract

Previous papers (Avery [2], Daniel and Hirshleifer [8]) conclude that seller's revenue decreases when jump-bidding occurs, which is in sharp contrast to the fact that jump-bidding is allowed rather than forbidden by sellers in real-life auctions (e.g., Sotheby's auctions, the FCC spectrum auctions). In our study, we conduct experiments of private value auctions and find that sellers' revenue actually increases significantly when jump-bidding occurs. We provide a theory regarding jump-bidding in which the revenue in jump-bidding equilibria dominates that in the no-jump equilibrium, when bidders are risk-averse. The experimental outcomes are consistent with our theory.

Keywords: English auction, jump-bidding, risk aversion, laboratory experiment

JEL classification: C12; C90; D44; D82

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"A collective gasp swept the ballroom as the first round of results was announced: Bidding had started at $20 million each for two licenses and $10 million for five others. That was several times the sum that the experts had projected for the first round." The Washington Post, July 26, 1994, p. D1, on the Nationwide Narrowbank PCS auction in July 1994

1 Introduction

A fundamental question in economics is how prices are formed in markets. Auctions provide an excellent framework to study this question. To sell an object in an auction, sellers choose the optimal auction rule to maximize profits, and buyers choose the optimal strategies to compete to win the object. That is, the price of the object sold is a result of the interaction between sellers and buyers.

In an ascending-price auction, the price gradually increases in fixed increments. During the auction, however, any bidder may call out a price that is much higher than the current price plus the increment. This "*jump-bidding is an endemic feature of real-world ascending auctions, including not only FCC wireless spectrum auctions but also online (eBay) auctions and conventional art and antiques auctions run by Sotheby's and Christie's for hundreds of years*" (Grether, Porter, and Shum [12]). For example, Cramton [6] documents that in an FCC radio spectrum auction, forty-nine percent of the new bids are jump bids.[1]

Why do bidders raise their prices voluntarily? An answer may be found in one of the most famous examples of jump-bidding, as described below by Avery [2].

An infamous recent example occurred in 1988 when Ross Johnson, the CEO of RJR Nabisco, made a bid of $75 for the shares of his own company when the stock was trading at $55. In further competition. . . Kohlberg, Kravis and Roberts (KKR) raised Johnson's bid to $90. KKR won the bidding at a final price of $106 after only a few more rounds of bidding. Later, George Roberts admitted that his company would not have competed if Johnson had started with a higher opening bid of $90 or more.

[1] Avery [2], Cramton [5], [6], Daniel and Hirshleifer [8] offer numerous real-life jump-bidding examples.

By jump-bidding to a high price, a bidder may have to bear the cost of paying more than necessary; however, the bidder may receive the benefit of driving his opponents to quit earlier in the bidding than they otherwise would have. When the latter force dominates the former one, jump-bidding occurs. Daniel and Hirshleifer [8] suggest that bidding is costly, and bidders jump bid and quit early to reduce costs[2]; Avery [2] suggests that the phenomenon known as winner's curse drives jump-bidding.[3] Until recently, researchers have had a fairly good understanding of jump-bidding, albeit on the buyers' side; however, the situation is much less clear on the sellers' side. In particular, current theories (e.g., the two papers cited above) suggest that jump-bidding reduces sellers' revenue, a suggestion that is in sharp contrast to the fact that jump-bidding continues to be encouraged rather than forbidden by auctioneers worldwide. This issue therefore begs the question:

$$\text{Does jump-bidding increase sellers' revenue?} \qquad (\star)$$

If the answer to this question is no, then all auctioneers should forbid jump-bidding; if the answer is yes, then something is clearly missing in our understanding of jump-bidding. Thus, the objective of this paper is to answer the question in ($\star$). To the best of our knowledge, little empirical and experimental research has been undertaken on this question, and we are the first to design lab experiments to answer this question.[4] Compared to other methodologies (e.g., empirical analysis, field experiments), lab experiments are able to fully control all other economic factors except jump-bidding and to distill the pure revenue effect of jump-bidding.[5]

We focus on an independent-private-value (hereafter, IPV) setup, and our experi-

[2]Daniel and Hirshleifer [8] consider an auction with sequential bids and construct an equilibrium in which the first bidder uses a monotonic bidding strategy that fully reveals his/her value to the second bidder. After observing a bid from the first bidder, the second bidder may understand that there is no chance to win and thus want to quit early to reduce the bidding costs.

[3]By jump-bidding, a bidder signals his intent to follow a more aggressive strategy. As a result, his competitors choose a less aggressive strategy and quit early because of winner's curse.

[4]Isaac, Salmon, and Zillante [16] are the first researchers to use laboratory experiments to test various jump-bidding models. Their study, which focuses on jump-bidding on the bidders' side, indicates that the jump-bidding observed in field auctions is likely linked to bidders' impatience. Recently, Grether, Porter, and Shum [12] adopt the field experiment approach and manipulate the price grid, the possible amounts that bidders can bid above the current price, in online auction sites that sell used automobiles via ascending auctions. These researchers find peculiar patterns of bidding that suggest that they are "cyber-shills" working on behalf of sellers.

[5]Another potential difficulty in other methodologies is regarding how to estimate value distribution from the jump prices, which is necessary to determine the revenue effect of jump-bidding.

mental data show that jump-bidding significantly increases sellers' revenue. More precisely, at the 2% significance level, the Mann-Whitney test rejects the null hypothesis that jump-bidding does not affect sellers' revenue, in favor of the alternative that jump-bidding increases sellers' revenue, i.e., with probability 0.98, we are certain that the effect of jump-bidding on revenue is positive. Section 2 provides a detailed summary of our experimental results, followed by a full description of our experimental design in Section 4 and findings in Section 5 and 6.

To understand the positive revenue effect of jump-bidding, we elicit bidders' risk attitudes in our experiments. We find the following two stylized facts: (1) the majority of bidders are risk-averse, and (2) bidders who jump substantially more than others tend to exhibit increasing or constant absolute risk aversion (IARA/CARA).[6] Based on these observations, we propose a novel theory by associating jump-bidding with risk attitudes.

To illustrate this idea, consider the following example of an English auction with the uniform prior. Consider the possibility that jumping from the current price of \$0 to \$700 can signal that one's value is greater than or equal to \$1,000. Suppose my value of the object for sale is $\$1,000$. By viewing such a signal, all of my competitors with values of less than $\$1,000$ would quit immediately, because they expect to have no chance to win. By paying a price of \$700, I receive a benefit by deterring my competitors with values up to $\$1,000$; therefore, I prefer jump-bidding. To make the above example an equilibrium, the signaling must be credible (i.e., I prefer not to jump bid if my value is less than $\$1,000$), which can be supported by certain particular risk attitudes. For example, the non-decreasing absolute risk aversion introduced in McAfee and Vincent [22] is sufficient to support the equilibrium described above. Furthermore, suppose I am risk-averse. In that case, jump-bidding serves as insurance: for both jumping and not jumping, I win the same group of opponents (i.e., bidders with value less than $\$1,000$), but I pay a fixed price of \$700 for jumping rather than a random winning price between \$0 and $\$1,000$ (with the expected value \$500) for not jumping. Hence, by jump-bidding, I take the insurance and surrender some risk premium ($\$200 = \$700 - \$500$) to the seller. As a result, the seller's revenue increases.

[6]More precisely, our experimental data show that, among the bidders whose risk attitudes are identified, 89% are weakly risk-averse and 67% of them are either CARA or IARA.

Methodologically, we make one contribution in experimental design. Note that a well-documented phenomenon in IPV auction experiments is overbidding, i.e., bidders stay in an auction even if the prices exceed their values (Kagel, Harstad, and Leven [19], Kagel and Levin [18], Harstad [14]). However, as shown in Kagel, Harstad, and Levin [19] and Garratt, Walker and Wooders [10], overbidding is common only among inexperienced bidders and tends to be a short-term phenomenon.[7] Hence, to understand the revenue impact of jump-bidding, we must eliminate overbidding. Previous papers (Andreoni, Che and Kim [1], Cooper and Fang [4]) suggest that overbidding is primarily driven by bidders' spitefulness, i.e., bidders want to hurt the interests of their opponents (even if they may incur a loss themselves).[8] We aim to eliminate overbidding by designing an *amended* random payment scheme: 10 rounds of English auctions are conducted, and only one round is randomly and independently chosen to be the payment round for each bidder, i.e., each bidder's final payoff depends only on the outcome of the auction in his payment round.[9] Furthermore, none of the bidders knows his payment round, and hence, in every round, every bidder attempts to maximize profit. However, we amended the standard random payment scheme by allowing every bidder to *know* whether each round is a payment round of his opponent. As a result, in every non-payment round of the opponent, the spitefulness concern is fully eliminated for every bidder. Our experiment data show that such an amended random payment scheme eliminates 76% of the overbidding.

The remainder of the paper proceeds as follows. Section 2 provides a summary of the experimental results. In Section 3, we present the model of jump-bidding with risk aversion. In Section 4 and 5, we discuss the experimental design and findings, respectively. Section 6 presents our new experimental design to control for the overbidding

[7]Malmendier and Lee [20] empirically identify overbidding in eBay auctions by comparing online auction prices to fixed prices for the same item on the same website. Although only a small fraction of bidders are identified as overbidders, these bidders generate a large fraction of auctions with overbidding. The results are explained by limited attention.

[8]Section 5 presents data from three treatments with no experimental control for overbidding and shows that actual revenues from the treatments with and without jump-bidding are not significantly different. Our exit-survey results reveal that overbidding is indeed primarily induced by spitefulness.

[9]This "random lottery incentive system" is widely used in experimental economics to motivate subjects. Cubitt, Starmer and Sugden [7] provide evidence for the validity of the incentive system. Azrieli, Chambers and Healy [3] show that under a mild assumption imposed on subjects' preference, the random lottery incentive system is the only incentive-compatible mechanism.

behavior and discusses its results. Section 7 concludes. A review of the related literature is presented in the reminder of this section.

1.1 Related Literature

This section is devoted to the review of the related literature. In particular, we discuss several theoretical and experimental papers that attempt to explain why buyers participate in jump-bidding.

Easley and Tenorio [9] study internet auctions and explain jump-bidding by entry costs and uncertainty about future entries. Gunderson and Wang [13], Hörner and Sahuguet [15] and Zheng [25] also construct jump-bidding equilibria in private-value models. Gunderson and Wang [13] assume a disconnected support of bidders' values and suggest that jump-bidding is a signal of high value. Instead of focusing on why people engage in jump-bidding, Hörner and Sahuguet [15] examine how *bluffing* and *sandbagging* (i.e., non-monotone bidding strategies) are implemented in jump-bidding. Zheng [25] considers multi-unit auctions and studies jump-bidding as a signaling device across auctions. In all of these papers, jump-bidding is regarded as the bidder's signal. The difference among them is what makes the signaling credible. We relate jump-bidding to risk attitudes and offer a novel explanation.

In an interesting paper, Goeree [11] studies a modified English auction followed by aftermarket competition.[10] Bidders signal high values in the English auction to gain an advantage in the aftermarket, and sellers' revenue increases as a result. Signaling occurs only when all bidders but one have dropped out of the auction, with the final bidder remaining in the auction until the price reaches the optimal signaling value. However, under the traditional English auction rule that we consider, such signaling is excluded because the auction ends immediately when only one bidder remains.

Other authors explain jump-bidding using behavioral reasons. Rothkopf and Harstad [24] attribute jump-bidding partially to bidders' irrationality. Although Isaac, Salmon,

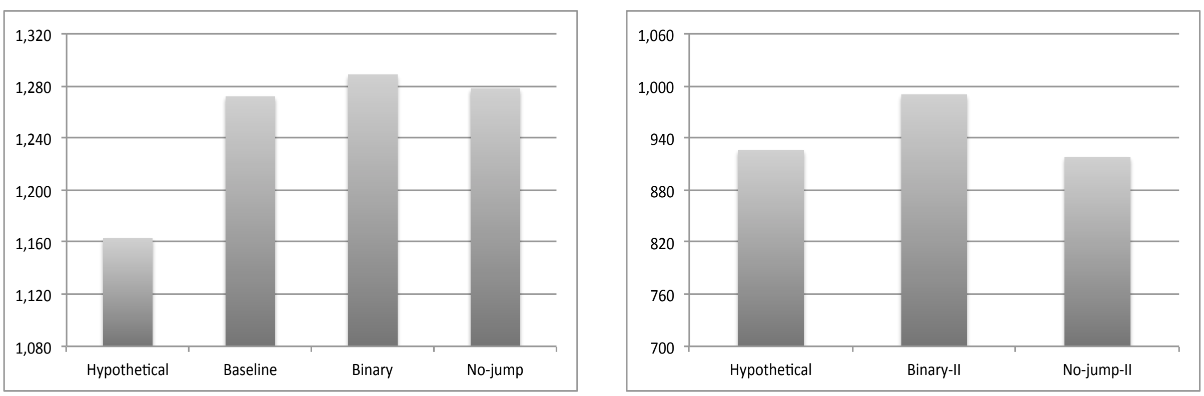
[10] The main objective of Goeree [11] is to compare signaling effects in first-price, second-price and English auctions when aftermarket competition exists.

and Zillante [17] model jump-bidding as a strategic dynamic game, information updating in this game is non-strategic.[11] Malmendier and Lee [20] propose that people may bid above their true values for behavioral reasons: limited memory, limited attention, joy of winning, etc. Isaac et al. [16] use experiments to test various jump-bidding models, finding that the jump-bidding observed in field auctions is likely the result of bidders' impatience.

2 Summary of Experimental Results

In this section, we summarize our experimental findings, including four noteworthy points.

Finding 1. *Jump-bidding increases revenue.*



(a) Standard Design (b) Amended Random Payment Design

Figure 1: Revenue Comparison

In a standard IPV English auction (without jump-bidding), bidding one's true value is a weakly dominant strategy. As a result, the auction outcome is that the highest-valued bidder wins at the price of the second-highest value, which is called the *hypothetical price*. Usually (e.g., in Daniel and Hirshleifer [8] and Hörner and Sahuguet [15]), the hypothetical price is used as a benchmark to compare the revenue for allowing jump-bidding.

[11] In the model of Isaac et al. [17], after seeing a jump bid of p from bidder $-i$, bidder i forms a naive belief of $[v_{-i} \geqslant p]$, although only bidders $-i$ with $v_{-i} \geqslant \overline{v} > p$ make such a jump in equilibrium, i.e., bidders do not use Bayesian update information according to equilibrium strategy profile and all prior information.

That is, jump-bidding increases (decreases) the revenue if and only if the expected price induced by a jump-bidding equilibrium is larger (smaller) than the hypothetical price.

In our first two treatments (*Baseline* and *Binary*), we conducted a clock auction that allowed jump-bidding in two different conditions.[12] Figure 1(a) compares the jump-bidding revenue and the hypothetical revenue. Clearly, jump-bidding increases the revenue. However, as a robustness check, we also conducted a standard clock auction without jump-bidding (*No-jump* treatment). Figure 1(a) also compares the revenues for jump-bidding, no jump-bidding, and the hypothetical price.

Note that the revenue for no-jump is also significantly higher than the hypothetical price, and there is no statistically meaningful difference between jump-bidding (*Baseline* and *Binary*) and *No-jump*. Overbidding evidently exists, and as a result, our data are not able to show the *pure* revenue effect of jump-bidding. This observation leads us to design two new treatments (*Binary-II* and *No-jump-II*) with an additional experimental control implemented by the *Amended Random Payment* (ARP) design discussed in the introduction to eliminate the overbidding, which eliminates 76% of the overbidding. Figure 1(b) compares the resulting revenues for jump-bidding, no-jump, and the hypothetical price in the new design. The results clearly show

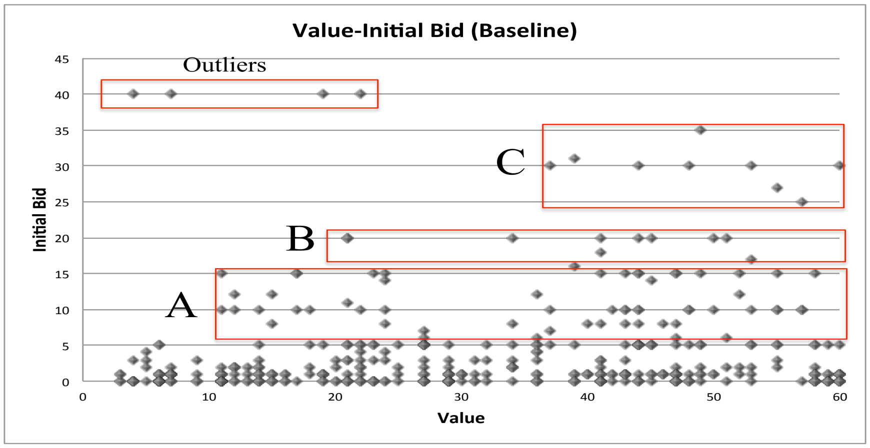
$$\text{Revenue for Jump-bidding} > \text{Revenue for No-jump} \approx \text{Hypothetical Revenue.}$$

Finding 2. *Jump-bidding signals high values.*

Figure 2 presents a scatter diagram between bidder values and jump bids in our *Baseline* treatment, in which any integer number between 0 and 60 is allowed for a jump bid. It is clear that jump-bidding at 5 or below is not informative. There appear to be three clusters of informative jump-bidding. First, jump-bidding at 10 ($\pm$5) primarily comes from the value range between 10 and 60 (Region A). Second, jump-bidding at 20 ($\pm$2) is primarily from the value range between 20 and 50 (Region B). Third, jump-bidding at 30 ($\pm$5) is primarily from the value range between 35 and 60 (Region C). That is, jump-bidding is informative, albeit not fully.

[12] Section 4 presents a full description of our experimental design.

Figure 2: Jump-bidding and Values



In our *Binary* treatment in which either 0 or 20 is allowed for a jump bid, we also find that jump-bidding is informative, as we have

$$E\left[\text{Value} \mid \text{Jump}\right] > E\left[\text{Value}\right] > E\left[\text{Value} \mid \text{No-jump}\right].$$

Finding 3. *Bidders who jump substantially more than others tend to exhibit increasing or constant absolute risk aversion (IARA/CARA).*

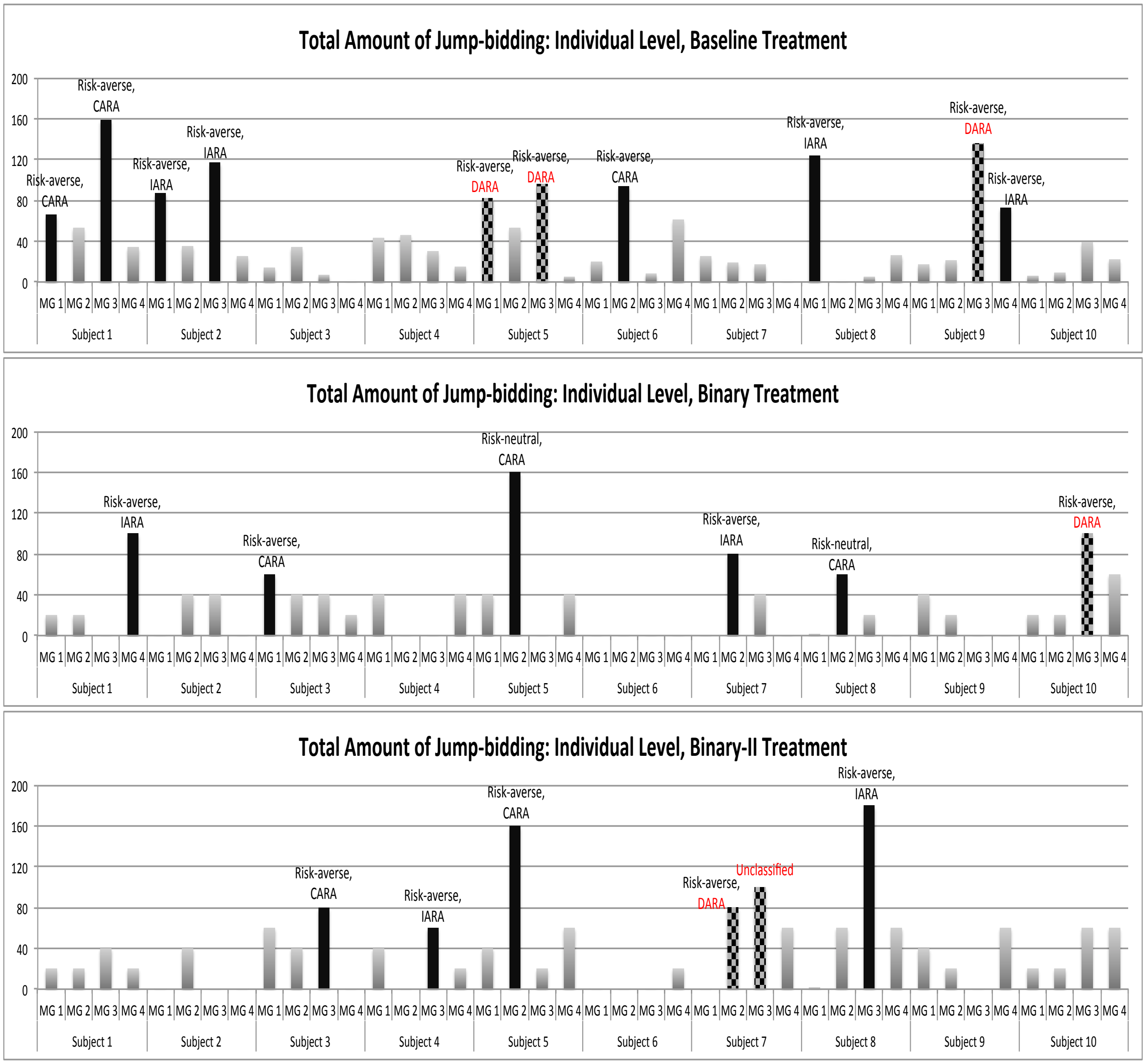
Figure 3 reports the individual level total amount of jump-bidding in the three treatments with jump-bidding. For individuals who jump substantially more than others, the elicited risk attitude is also presented. These bidders tend to exhibit increasing or constant absolute risk aversion (highlighted by dark bars in Figure 3), with the exception of only a few cases (highlighted by checked bars in Figure 3).[13]

Finding 4. *Jump-bidding significantly increases revenue for risk-averse bidders.*

Figure 4 reports the (average) normalized actual revenue (= Actual Revenue - Hypothetical Revenue) aggregated across all rounds for all individuals with the same elicited

[13] At the end of each session, we elicited the risk attitude of each individual according to Table 10 (Small Stake: $Y = 10$ and $h = 4$ / Large Stake: $Y = 30$ and $h = 4$) in Appendix A. Appendix D presents the experimental instructions and screen shot. Note that when subjects make decisions in the auction game, we do not inform them that they will have additional tasks. The risk attitudes of 87% of the subjects are identified. Among the identified subjects, 67% of them are classified as risk-averse with CARA or IARA. Figure 11 and Table 11 in Appendix A report elicited risk attitudes at the aggregate level and the individual level, respectively.

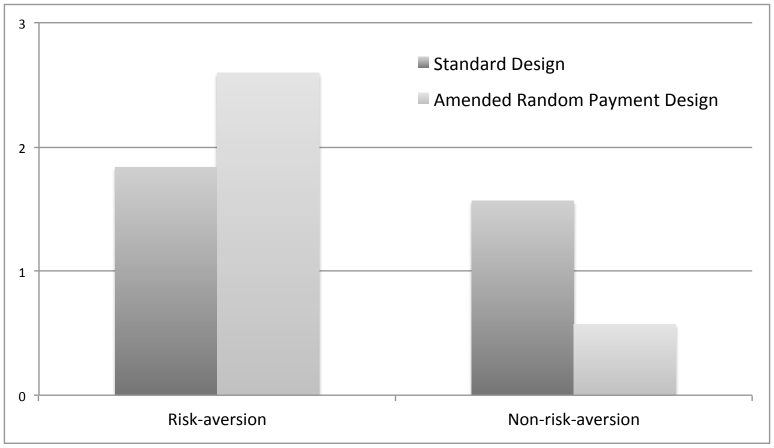
Figure 3: Jump-bidding and risk attitude



risk attitude. The first column presents the normalized actual revenue for risk-averse bidders and the second column for all the other bidders. The dark bar and the light bar represent data from the treatments using the standard design (*Baseline* and *Binary* treatments) and the ARP design (*Binary-II* treatment), respectively.

Clearly, the normalized actual revenue for risk-averse bidders is significantly larger than 0 in both designs. More precisely, we can reject the null hypothesis that the actual revenue for risk-averse bidders is the same as the hypothetical revenue in favor of the alternative that the actual revenue for risk-averse bidders is larger than the hypothetical

Figure 4: Revenue and risk attitude



revenue (one-sided Mann-Whitney test, $p = 0.08575$).

Furthermore, the normalized actual revenue for risk-averse bidders is higher than that of non-risk-averse bidders. Although the difference is not statistically significant in the standard design (two-sided Mann-Whitney test, $p = 0.8218$), the difference becomes significantly larger in the ARP design: the one-sided Mann-Whitney test reveals that the normalized actual revenue for risk-averse bidders is significantly larger than that of non-risk-averse bidders with $p = 0.0826$.

3 A Theory of Jump Bidding

We present a theory which is consistent with the findings described in Section 2. For simplicity, we consider a 2-bidder IPV model.[14] One indivisible object is for sale, with bidders 1 and 2 having values v_1, v_2, respectively. The values have an i.i.d. distribution on the support $[0, 1]$ with cdf $F(\cdot)$. Let bidder $-i$ denote bidder i's opponent. The two bidders are expected utility maximizers with the same differentiable and strictly increasing Bernoulli utility function $u(\cdot)$. We normalize $u(0)$ to 0. Suppose $u'''(t)$ exists. We list a

[14]The model, as well as all the analytical results, can be straightforwardly extended to the case with more than two bidders.

few assumptions on risk attitudes as follows.

$$\text{risk-neutral bidders: } u''(t) = 0; \quad \text{risk-averse bidders: } u''(t) < 0,$$
$$\text{CARA bidders: } \frac{d\left(-\frac{u''(t)}{u'(t)}\right)}{dt} = 0; \qquad \text{IARA bidders: } \frac{d\left(-\frac{u''(t)}{u'(t)}\right)}{dt} > 0.$$

Following Avery [2], we model the auction by a 2-stage game: the jump stage (i.e., stage 1), followed by a standard clock auction (i.e., stage 2).[15] In stage 1, each bidder i chooses $\beta_i \in [0,1]$; in stage 2, an English auction with the starting price $\max\{\beta_i, \beta_{-i}\}$ is conducted, and each bidder i chooses the price $b_i(\beta_i, \beta_{-i}, v_i) \geqslant \max\{\beta_i, \beta_{-i}\}$ to exit. A winner gets utility $u[v_i - b_{-i}(\beta_i, \beta_{-i}, v_{-i})]$, and his opponent (i.e., the loser) gets 0. Bidder i wins if $b_i(\beta_i, \beta_{-i}, v_i) > b_{-i}(\beta_i, \beta_{-i}, v_{-i})$. A tie occurs if and only if $b_i(\beta_i, \beta_{-i}, v_i) = b_{-i}(\beta_i, \beta_{-i}, v_{-i})$. If $b_i(\beta_i, \beta_{-i}, v_i) = b_{-i}(\beta_i, \beta_{-i}, v_{-i}) = \beta_i > \beta_{-i}$, bidder i wins. For all other cases of tie, a fair coin determines the winner.

Throughout the paper, we adopt the solution concept of perfect Bayesian equilibrium (PBE). As a benchmark, the usual no-jump equilibrium is defined as follows.

$$\widehat{\sigma}_i : \begin{pmatrix} \text{stage 1: } \beta_i = 0; \\ \text{stage 2: } b_i(\beta_i, \beta_{-i}, v_i) = \max\{\beta_i, \beta_{-i}, v_i\}. \end{pmatrix}$$

Following $(\widehat{\sigma}_1, \widehat{\sigma}_2)$, no one jumps in stage 1, and each bidder stays in the auction in stage 2 until the price reaches her true value. The usual argument shows that $(\widehat{\sigma}_1, \widehat{\sigma}_2)$ is a PBE.

Proposition 1 (no-jump PBE)**.** *$(\widehat{\sigma}_1, \widehat{\sigma}_2)$ is a PBE.*

We now define a class of jump-bidding equilibria. For any $v \in [0,1]$, define $k(v) \in [0,1]$ to be the unique number satisfying[16]

$$F(v)u(v - k(v)) = \int_0^v u(v - v')dF(v'). \tag{1}$$

[15] Looking at the two-stage game of jump-bidding is one of the simplest possible ways to understand the role of jump-bidding in the seller's revenue. However, it is straightforward that the model can be extended to the version with multiple rounds of jump-bidding with all the analytical results and the intuition being preserved.

[16] $F(v)u(v-y)$ is strictly decreasing in y. Since $F(v)u(v-0) \geqslant \int_0^v u(v-v')dF(v') \geqslant F(v)u(v-v)$, there exists a unique $k(v)$ for each $v \in [0,1]$ such that equation (1) is satisfied.

Fix any $(v^*, k(v^*)) \in (0,1) \times (0,1)$, we construct a jump-bidding equilibrium (σ_1^*, σ_2^*) as follows.

$$\sigma_i^* : \left(\begin{array}{c} \text{stage 1: } \beta_i = \begin{cases} 0, & \text{if } v_i < v^*; \\ k(v^*), & \text{if } v_i \geqslant v^*. \end{cases} \\ \text{stage 2: } b_i(\beta_i, \beta_{-i}, v_i) = \begin{cases} \max\{\beta_i, \beta_{-i}\}, & \text{if } \beta_{-i} = k(v^*) \text{ and } v_i < v^*; \\ \max\{\beta_i, \beta_{-i}, v_i\}, & \text{otherwise.} \end{cases} \end{array} \right)$$

By following σ_i^*, the high types of bidder i (i.e., $v_i \geqslant v^*$) jump to $k(v^*)$ in stage 1, and the low types of bidder i (i.e., $v_i < v^*$) do not jump. I.e., bidder i uses the jump bid $k(v^*)$ to signal his high values. In the case that $\beta_{-i} = k(v^*)$ and $v_i < v^*$, bidder i infers that $v_{-i} \geqslant v^*$ and expects no chance to win, and hence, bidder i quits immediately. For any other cases, bidder i follows the weakly dominant strategy $b_i(\beta_i, \beta_{-i}, v_i) = \max\{\beta_i, \beta_{-i}, v_i\}$ in the clock auction in stage 2.

Proposition 2. *(σ_1^*, σ_2^*) is a PBE for risk-neutral, CARA and IARA bidders.*

Proposition 2 is consistent with Findings 2 and 3. We provide an intuition of the proof here. To make (σ_1^*, σ_2^*) a PBE, the jump bid must be credible, i.e., the high types prefer "jumping to $k(v^*)$" to "no jump," and the low types prefer "no jump" to "jumping to $k(v^*)$. First, consider the threshold type v^*, and for both options, she wins the auction if and only if $v_{-i} \leqslant v^*$. And, the only difference is that she wins at the fixed price $k(v^*)$ for "jumping to $k(v^*)$," while she wins at a random price $v_{-i} \sim [0, v^*]$ with cdf $\frac{F(v_{-i})}{F(v^*)}$ for "no jump." By (1), $k(v^*)$ is defined to make type v^* indifferent between the two options. Second, consider a high-type bidder i (i.e., $v_i > v^*$), and she is facing exactly the same dilemma as type v^*: conditional on $v_{-i} \leqslant v^*$, she wins at the fixed price $k(v^*)$ for "jumping to $k(v^*)$," while she wins at a random price $v_{-i} \sim [0, v^*]$ with cdf $\frac{F(v_{-i})}{F(v^*)}$ for "no jump."[17] Given CARA/IARA, this high type is weakly/strictly more risk-averse than type v^*, i.e., she is willing to sacrifice weakly/strictly more to eliminate the same risk. Hence, this high type weakly/strictly prefers "jumping to $k(v^*)$" (i.e., the fixed price $k(v^*)$) to "no jump" (i.e., the random price $v_{-i} \sim [0, v^*]$ with cdf $\frac{F(v_{-i})}{F(v^*)}$). Similarly, a

[17]Conditional on $v_{-i} > v^*$, the two options induce the same outcome.

CARA/IARA low type (i.e., $v_i < v^*$) weakly/strictly prefers "no jump" to "jumping to $k(v^*)$."

The following theorem explains why jump bidding increases revenue, and it is consistent with Findings 1 and 4.

Theorem 1 (seller's revenue)**.** *Given risk-averse bidders, the seller has more expected revenue in (σ_1^*, σ_2^*) than in $(\widehat{\sigma}_1, \widehat{\sigma}_2)$.*

The intuition of Theorem 1 is straightforward: jump-bidding serves as insurance. By jump bidding, high types (of bidder i) pay the fixed price $k(v^*)$ to insure themselves against random winning price $v_{-i} (\leqslant v^*)$. If the bidders are risk-averse, they surrenders risk premium to the seller.

Furthermore, both bidders are weakly better-off in the jump-bidding equilibrium. Let $Eu_i(v_i|\varepsilon_i, \varepsilon_{-i})$ denote the expected utility of bidder i with value v_i, when the strategy profile $(\varepsilon_i, \varepsilon_{-i})$ is chosen by the two bidders.

Theorem 2 (bidder's welfare)**.** *For a PBE (σ_1^*, σ_2^*), $Eu_i\left(v_i|\sigma_i^*, \sigma_{-i}^*\right) \geqslant Eu_i\left(v_i|\widehat{\sigma}_i, \widehat{\sigma}_{-i}\right)$ for every $i \in \{1, 2\}$ and every $v_i \in [0, 1]$.*

Theorems 1 and 2 suggest that the jump-bidding equilibrium (σ_1^*, σ_2^*) is (ex-ante and interim) weakly Pareto superior to the no-jump equilibrium $(\widehat{\sigma}_1, \widehat{\sigma}_2)$.[18] Therefore, it is theoretically more appealing to select the jump-bidding equilibrium, which is indeed consistent with our experimental data showing the prevalence of jump-bidding.

4 Experimental Design

For our experimental implementation, we consider a 2-bidder IPV model. One indivisible object is for sale, with bidders 1 and 2 having values. We model the auction by a 2-stage

[18] As will be clear in Section 5.1, we observed in our data that subjects overbid due to a spite concern. Our jump-bidding equilibrium (σ_1^*, σ_2^*) with the following slight modification predicts the observed behavior pretty well: First, high value bidders ($v_i \geqslant v^*$) jump to $k(v^*) - \delta$ with $\delta > 0$; low value bidders do not jump. Second, all bidders stay after observing the jump $k(v^*) - \delta$. Third, low value bidders quit at price $k(v^*)$; high value bidders stay after price $k(v^*)$. Thus, when $v_i \in [0, k(v^*))$, a spiteful behaviour is expected.

game: the jump stage (Stage 1), followed by the bidding stage (Stage 2). In Stage 1, each bidder simultaneously chooses the initial bid; in Stage 2, a standard English auction with the starting price at the maximum of the initial bids is conducted, and each bidder chooses the price to exit.

We design our experiments to capture the standard model of jump-bidding in the literature. There are in total three treatments as summarized in Table 1.

Table 1: Experimental Treatments

	Baseline	*Binary*	*No-Jump*
Jump Bidding	Any integer in $[0, 60]$	0 or 20	Not Allowed

For our experimental implementation, we used the uniform value distribution over the support $\{0, 1, ..., 60\}$. The three treatments differ only with respect to what has been allowed in Stage 1. In the baseline treatment, individuals are allowed to make an initial bid, any integer in $[0, 60]$ inclusively. In *Binary* treatment, the initial bid is a binary choice between 0 and 20.[19] In the No-Jump treatment, the initial jump-bid is not allowed, i.e. the initial bid must be 0.

4.1 Experimental Procedure

The experiment was conducted in English using z-tree (Fischbacher, 2007) at the Hong Kong University of Science and Technology Experimental Laboratory. Two sessions each for *Baseline* and *Binary* treatments and three sessions for *No-jump* treatment were conducted using a between-subject design. Each session involved two independent matching groups, each of which has five pairs of two individuals. In total, 140 subjects participated

[19] There are two reasons to have *Binary* treatment in our design although having the binary options for the initial bid does not look very natural. First, it is standard in the literature (e.g. Avery, 1998) to model the jump-bidding by having an initial-bid stage with only binary options. Second, the more natural setup with multiple options in the initial-bid stage as in our *Baseline* treatment may suffer from the multiple equilibria problem due to the fact that we are free to choose the out-of-equilibrium belief for any initial bid never made in equilibrium. By having the binary options only, we would like to get rid of the multiple equilibria problem and make a certain initial bid more focal.

in 7 sessions.[20] Subjects had no prior experience in our experiments and were recruited from the undergraduate / graduate population of the university.

Upon arrival at the lab, subjects were instructed to sit at separate computer terminals. Each was given a copy of the experimental instructions (see Appendix B). Instructions were read aloud and supplemented by slide illustrations. In each session, subjects first participated in one practice round and then 10 official rounds. A random matching protocol was used.

We illustrate the instructions for *Baseline* treatment. The full instructions are attached in Appendix B. At the beginning of each round, the computer randomly drew a value for each individual with equal probabilities in the range between 0 and 60.[21] Each subject is privately informed about his/her own value but not others. In each round, each subject is endowed with 60 tokens and is asked to make a bid to win an auction that consist of the following two stages: Initial Bidding Stage (Stage 1) and Price Clock Stage (Stage 2).[22]

In the initial bidding stage, subjects are asked to place an initial bid, any integer number between 0 and 60 inclusively.[23] The maximum of initial bids in a pair will become the initial price in the second stage. After all subjects submit their initial bids, the initial price will be announced for each pair and they are asked to stay with the screen for a number of seconds, randomly determined between 5 seconds and 15 seconds, to think about what to do in the next stage. The waiting time is independent upon the initial bids. If one's submitted initial bid is strictly lower than his/her opponent's initial bid, he/she is asked to decide whether to continue or to opt out. If one opts out, his/her opponent wins the auction with the initial price. Otherwise, Stage 2 will be proceeded. If one submits an initial bid higher than or equal to one's opponent's initial bid, he/she will be asked to

[20]In section 6, we will present data from two additional treatments, each of which has two sessions. Including these four sessions with 80 additional subjects, we had 220 subjects participated in 11 sessions.

[21]Prior to the real experiment, we randomly and independently drew the set of values for each individual and for each round and used it for all sessions (and all matching groups) in order to have a tight revenue comparison among different treatments.

[22]Using an ascending clock procedure whereby the price of an item increased at small fixed increments has been one of the standard ways to implement an English auction in the laboratory since Kagel, Harstad and Levin (1987).

[23]In *Binary* treatment, however, only two options, 0 and 20, are given for the initial bid. No such stage exists in *No-jump* treatment.

click the continue button to proceed to Stage 2.

In the second stage, a price clock is presented in the decision screen that has three pieces of information: (1) initial price, (2) current price, and (3) your value. The price clock starts with the initial price determined in the initial bidding stage. The current price is displayed at the centre of the clock and in every two seconds, the clock goes and the current price increases in 1 unit. The value is highlighted in the clock with blue colour. Under the price clock a button "Not Interested Anymore" is in place. When one of the individuals in each pair clicks the button, the price clock stops and the auction ends. The individual who stays in the auction is declared the winner and pays the price showing on the clock. If no one drops out until the current price becomes 60, the auction ends and the final price becomes 60. In this case each individual has equal chance to win the auction. If one does not win the auction, the earning becomes the endowment 60 and otherwise the earning becomes endowment plus the value minus final price. At the end of each round, information feedback will be provided such as one's value, opponent's value, initial bid, opponent's initial bid, final price, auction outcome and final earning.

We randomly selected one round for real payment. A subject was paid the amount of token he or she earned in the selected round (1 token = 1 HKD) plus a HKD 30 show-up fee. Subjects earned on average HKD 140 ($\approx$ USD 18), ranging from HKD 126 to HKD 175.[24]

5 Experimental Findings

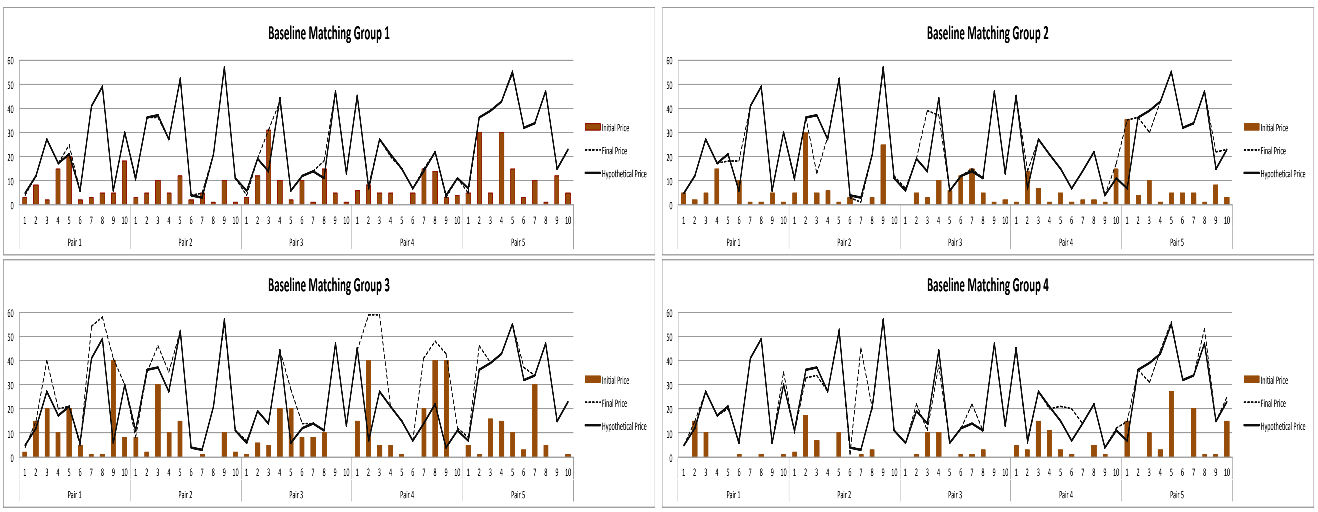
5.1 Bidding Behavior

We begin this section by drawing the reader's attention to Figures 5 and 6 below, which present subjects' bidding behaviors in *Baseline* and *Binary* treatments, respectively. Both Figures contain four panels with each panel referencing a different matching group. The horizontal axis of each panel consists of five blocks, each of which refers to each pair. On

[24] Under the Hong Kong's currency board system, the HK dollar is pegged to the US dollar at the rate of 1 USD = 7.8 HKD.

each block is the period ranging from 1 to 10. On the vertical axis are three different prices for a given pair in a given period. The three prices are Initial Price (IP) represented by the dark bar, Final Price (FP) represented by the thin dashed line, and Hypothetical Price (HP) represented by the solid line, where the initial price is the maximum of initial bids in a pair, the final price is the price at which the price clock stops, and the hypothetical price is the second highest value in each pair.[25] Note that the solid hypothetical price lines in all panels in all figures look the same because we used a common value distribution for all sessions and treatments.

Figure 5: Bidding Behaviors - *Baseline* Treatment



Four features of the data clearly emerge from both treatments. First, jump-biddings are prevailing. 85.5% of pairs in *Baseline* treatment and 28% of pairs in *Binary* treatment had a strictly positive initial price.[26] Second, most of the cases, 72% in *Baseline* treatment and 66% in *Binary* treatment, the final price is in the neighborhood (± 1) of the hypothetical price. Third, there are a few instances in which *overbidding* is observed, i.e. the final price is strictly higher than the hypothetical price. Fourth, there are a few instances in which *underbidding* is observed, i.e. the final price is strictly lower than the hypothetical price.[27]

[25]We call the second highest value in each pair the *hypothetical price* because if everyone hypothetically follows the weakly dominant strategy to wait until the price reaches one's value then the final price should be the second highest value in the pair.

[26]Paying attention to the jump-bidding significantly bigger than 0, we report that 32% of subjects in *Baseline* treatment made an initial bid weakly greater than 5.

[27]Precisely, we define overbidding (underbidding) as the case where the final price is strictly higher (lower) than the hypothetical price $+1$ (-1). This definition allows a small degree of mistake in the bidding behavior. More importantly, all findings of this paper are robust against the way we categorize different

Figure 6: Bidding Behaviors - *Binary* Treatment

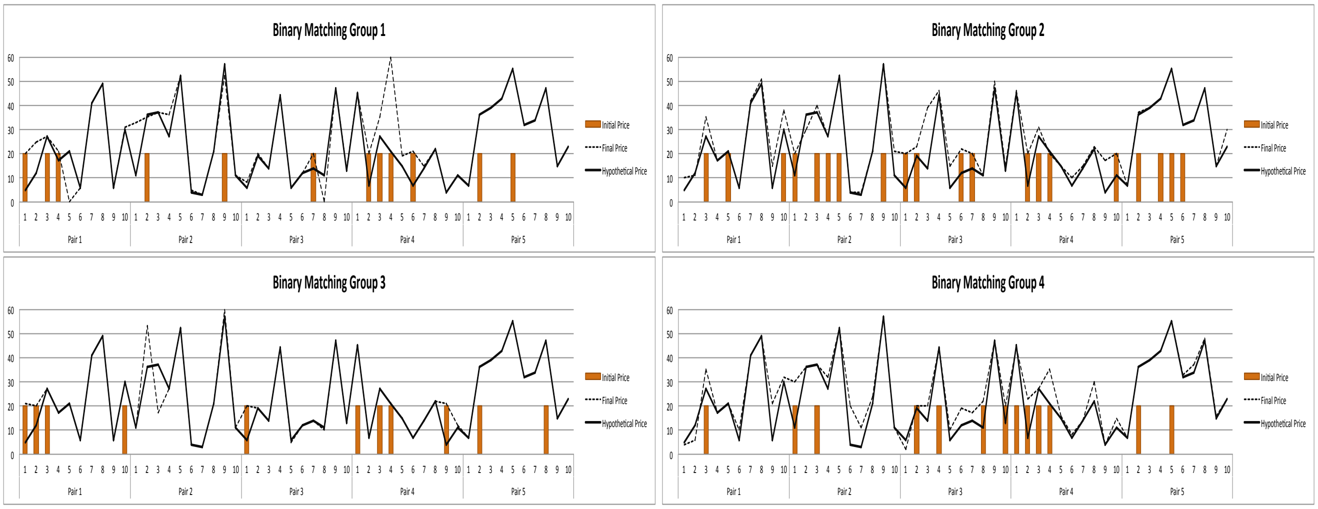


Table 2 provides a summary of the bidding behaviors in all three treatments.

Looking at Figures 5 and 6 more carefully, three different types of overbidding and underbidding are observed. First, there are a few instances in which over/underbidding is *directly* driven by jump-bidding, i.e. the initial price is the same as the final price which is strictly positive (e.g. Round 9 in Pair 1 of Matching Group 3, Baseline for overbidding / Round 1 in Pair 2 of Matching Group 3, Baseline for underbidding). Second, over/underbidding is sometimes *indirectly* driven by jump-bidding, i.e. the initial price is positive but the final price is strictly higher than the initial price (e.g. Round 3 in Pair 3 of Matching Group 2, Baseline for overbidding / Round 3 in Pair 2 of Matching Group 2, Baseline for underbidding). Third, over/underbidding occurs even when the initial price is 0 (e.g. Round 1 in Pair 2 of Matching Group 1, Binary for overbidding / Round 5 in Pair 2 of Matching Group 1, Binary for underbidding). Table 2 reports the frequencies of different types of overbidding and underbidding for each treatment. In both *Baseline* and *Binary* treatments, overbidding is more frequently observed than underbidding.

The bidding behaviors in *Baseline* and *Binary* treatments are qualitatively the same. The Kolmogorov-Smirnov test (KS test, hereafter) reveals that we cannot rejects the null hypothesis that the frequencies of overbidding not driven by jump-bidding in the two treatments are not significantly different (two-sided, $p = 0.699$).[28] The same test for all

bidding behaviors.

[28]This is due to the high variances in both frequencies, although the average frequency 8.25 from *Binary*

Table 2: Bidding Frequencies

		Baseline					*Binary*					*No-jump*						
Matching Group		1	2	3	4	Mean	1	2	3	4	Mean	1	2	3	4	5	6	Mean
FP= HP (±1)		44	39	31	34	37	35	26	43	28	33	24	33	24	36	26	34	29.5
OB	JB Direct	2	2	2	2	2	5	5	4	1	3.75	N/A						
	JB Indirect	2	3	10	1	4	2	6	0	5	3.25							
	No-jump	0	1	5	7	3.25	5	12	2	14	8.25	21	12	25	13	24	16	18.5
UB	JB Direct	2	1	1	2	2.5	2	0	0	0	0.5	N/A						
	JB Indirect	0	2	1	4	1.75	1	0	0	0	0.25							
	No-jump	0	2	0	0	0.5	0	1	1	2	1	5	5	1	1	0	0	2

Note: FP and HP refer to Final Price and Hypothetical Price, respectively. Similarly, OB, UB, and JB refer to Overbidding, Underbidding, and Jump-bidding, respectively. The same abbreviations apply to all other figures and tables hereafter.

other pairwise comparisons for the frequency of overbidding indirectly driven by jump-bidding, the frequency of underbidding indirectly driven by jump-bidding, and the frequency of underbidding not driven by jump-bidding gives us the same result with p-value at least 0.699. But the frequency of overbidding directly driven by jump-bidding looks slight higher and underbidding directly driven by jump-bidding looks slight lower in *Binary* treatment than in *Baseline* treatment, although the difference is not statistically significant (with $p = 0.105$ for both tests).

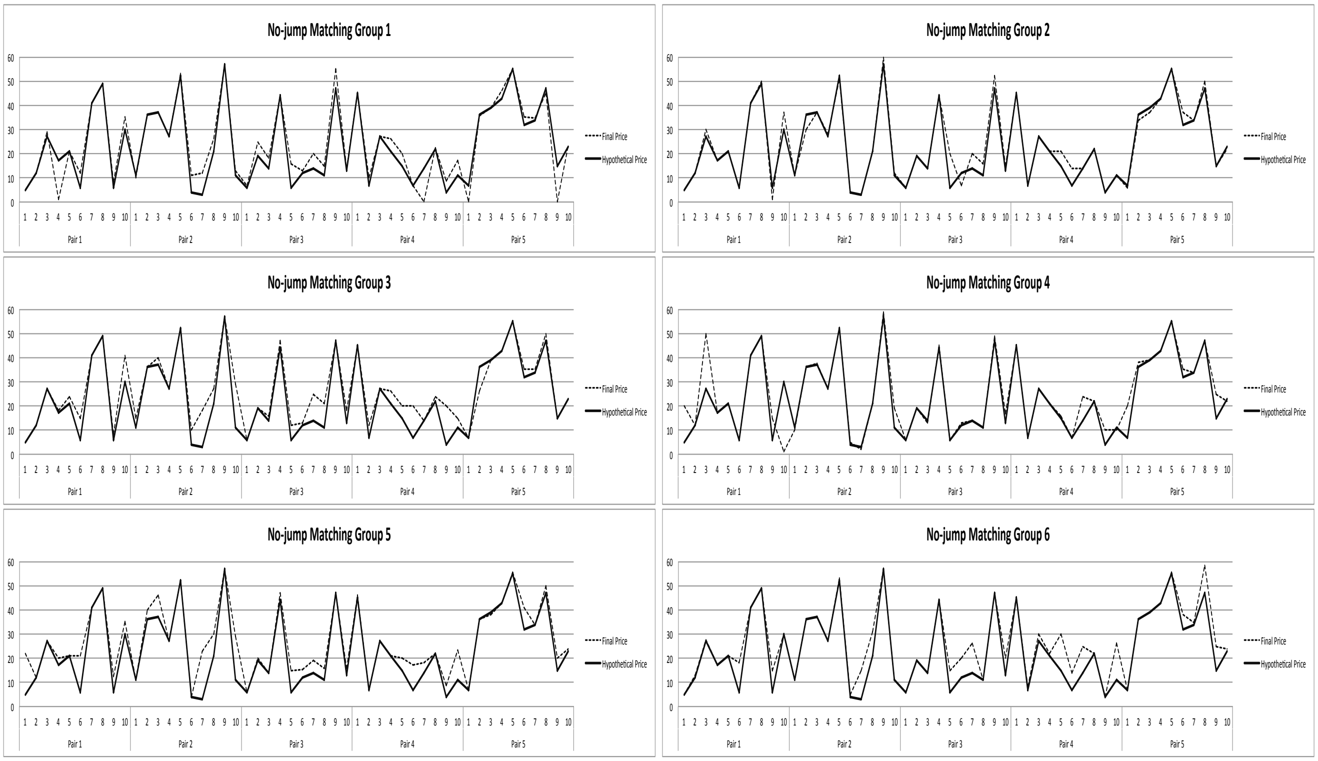
Result 1. *In Baseline and Binary treatments, jump-bidding directly and indirectly induces not only overbidding but also underbidding with a higher frequency of overbidding induced than underbidding.*

Table 3: Average Values Conditional on Initial Bids

Baseline Initial Bid	Frequency	Average Value
0	128	27.80
1 – 4	145	30.06
5 – 9	60	36.65
10 – 14	28	35.68
15 – 19	18	39.17
20 – 29	10	41.90
30 – 39	7	47.14
40	4	13
Binary Initial Bid	Frequency	Average Value
0	341	30.40
20	59	38.19
Unconditional		31.55

treatment seems to be a lot larger than 3.25 from *Baseline* treatment.

Figure 7: Bidding Behaviors - *No-jump* Treatment



Our data reveals that jump-bidding plays an informational role. Table 3 reports the average value of the opponent (v_{-i}) conditional on the initial bid being made for different ranges of it. In *Baseline* treatment, $E(v_{-i}|IB < 5) < E(v_{-i}) = 31.55 < E(v_{-i}|IB > 5)$ and the average values are almost monotonically increasing in the initial bid except that the average value of players who made initial bid 40 turns out to be 13 only. In *Binary* treatment, $E(v_{-i}|IB = 0) < E(v_{-i}) = 31.55 < E(v_{-i}|IB = 20)$.

We now present data from *No-jump* treatment in Figure 7. The figure contains six panels with each panel referencing a different matching group. There is no dark bar for the initial price because a positive initial bid is not allowed to be made in the treatment. A main feature emerging from the data is that a substantial degree of overbidding is observed (111 out of 300 observations) while some but very few underbidding is also observed (12 out of 300).[29] Table 2 also provides a summary of the bidding behaviors in *No-jump* treatment.

[29]The overbidding observed in the first two sessions (four matching groups) of *No-jump* treatment was an unexpected surprise to us and we had one more session (two matching groups) for a robustness check.

It is evident that overbidding is more prevailing in *No-jump* treatment than in the other two treatments.[30] The KS test reveals that the frequency of overbidding in *No-jump* treatment is significantly higher than the frequency of overbidding not driven by jump-bidding from *Baseline* treatment (one-sided, $p = 0.08$) and insignificantly higher than that from *Binary* treatment (one-sided, $p = 0.118$). However, there is no statistical difference (two-sided, $p > 0.699$; for all tests for pairwise comparisons) in the three treatments in terms of the frequency of underbidding (not driven by jump-bidding).

Result 2. *In all three treatments, a substantial degree of overbidding not driven by jump-bidding is observed with a significantly higher degree of overbidding observed in No-jump treatment than in the other two treatments.*

5.2 Revenue Analysis

Table 4 reports the result from a decomposition of the difference between the hypothetical and the actual revenues into the contributions from different types of bidding behaviors including over/underbidding directly/indirectly/not driven by jump-bidding. The *hypothetical* revenue is simply the sum of the hypothetical prices from all pairs and all rounds. There are a few findings emerging from the analysis of *Baseline* and *Binary* treatments. First, the actual revenue is significantly (one-sided KS test, $p < 0.01$) higher than the hypothetical revenue. Second, the revenue increase is partly due to the positive contributions from the overbidding directly and indirectly induced by jump-biddings. At the same time, there is non-negligible amount of revenue increased by overbidding not driven by jump-biddings. Third, underbidding has a negative but minor (relative to the overbidding) effect on the revenue. The actual revenues from the two treatments are statistically the same (two-sided KS test, $p = 0.699$).

[30] It is possible that the higher frequency of overbidding observed in *No-jump* treatment than in the other two treatments may be a consequence of the simplicity of the game the subjects played in *No-jump*. Without having the initial bidding stage, there is no concern about information transmission and the game remaining has the truthfully revealing weakly dominant strategy equilibrium. The equilibrium is quite intuitive and easy to understand, but does not allow a room for strategic interaction. As a result, subjects may feel bored easily and/or those who have a lower value (and realize that there is nothing they can do to win) may feel unfair, which may provoke some non-equilibrium behavior affected by other-regarding preferences. Note, however, that it is not our primary concern to understand why we have the asymmetric overbidding outcomes. In the next section, we shall instead propose a new experimental design to control for the overbidding and present experimental data from the design.

Table 4: Revenue Decomposition

		Overbidding			Underbidding			
Baseline	*Hypothetical*	JB Direct	JB Indirect	No-jump	JB Direct	JB Indirect	No-jump	*Actual*
Matching Group 1	1,163	+21	+11	+1	-3	-5	-3	1,185
Matching Group 2	1,163	+36	+26	+27	-1	-44	-3	1,204
Matching Group 3	1,163	+3	+236	+72	-4	-4	-1	1,465
Matching Group 4	1,163	+11	+4	+87	0	-25	-7	1,233
Mean	1,163	+17.75	+69.25	+46.75	-2	-19.5	-3.5	1,271.75

		Overbidding			Underbidding			
Binary	*Hypothetical*	JB Direct	JB Indirect	No-jump	JB Direct	JB Indirect	No-jump	*Actual*
Matching Group 1	1,163	+34	+65	+55	-32	-6	0	1,279
Matching Group 2	1,163	+51	+38	+95	-1	0	-7	1,339
Matching Group 3	1,163	+22	+33	+21	0	0	-22	1,217
Matching Group 4	1,163	+8	+68	+93	0	-1	-11	1,320
Mean	1,163	+28.75	+51	+66	-8.25	-1.75	-10	1,288.75

No-jump	*Hypothetical*	Overbidding	Underbidding	*Actual*
Matching Group 1	1,163	+109	-55	1,217
Matching Group 2	1,163	+69	-23	1,209
Matching Group 3	1,163	+173	-10	1,326
Matching Group 4	1,163	+110	-34	1,239
Matching Group 5	1,163	+188	0	1,351
Matching Group 6	1,163	+163	0	1,326
Mean	1,163	+135.34	-20.34	1,278

The bottom panel of Table 4 shows that the effect of overbidding on the revenue in *No-jump* treatment is positive and substantial. More importantly, the revenue increased by overbidding in *No-jump* treatment is significantly bigger than the revenue increased by overbidding not driven by jump-bidding in the other two treatments. Consequently, two-sided KS test indicates that we cannot reject the null hypothesis that the actual revenue from *No-jump* treatment is the same as that from *Baseline* treatment (two-sided, $p = 0.586$) and that from *Binary* treatment (two-sided, $p = 0.998$).

Result 3. *The actual revenue from No-jump treatment is not different from the actual revenue from Baseline and Binary treatments.*

On the one hand, our result from the revenue comparison already suggests that any existing theory may not be able to successfully organize our data since all existing papers predict that jump-bidding decreases the seller's revenue. On the other hand, there is a possibility that the revenue ranking becomes vague due to the overbidding behavior that may have heterogenous effects on the revenues for different treatments. Thus, it would be necessary to discuss the overbidding behavior more carefully and see if we can isolate the effect of jump-bidding on the seller's revenue from that of overbidding not driven by the jump-bidding.

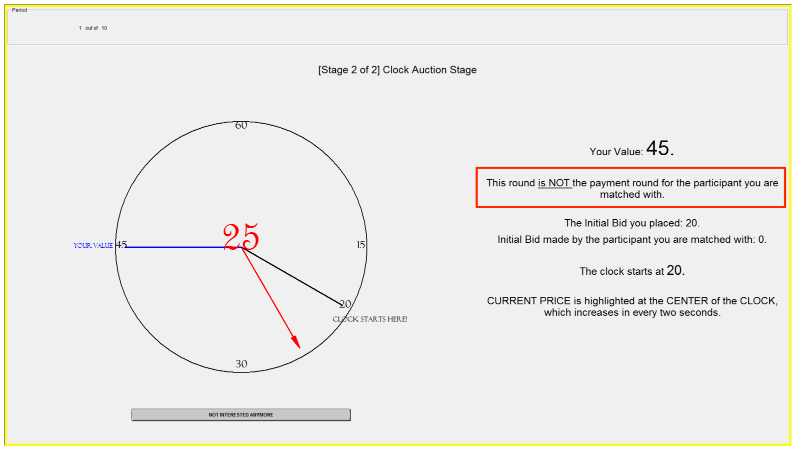
6 How to Control Overbidding? New Experimental Design and Its Results

Overbiddings in the second-price auctions and English auctions are well documented in the literature (Kagel, Harstad, and Leven, 1987; Kagel and Levin, 1993, Harstad, 2000). Why do people overbid? There are two competing hypotheses: Joy of winning hypothesis and Spite hypothesis (Andreoni, Che and Kim, 2007; Cooper and Fang, 2008). Joy of winning hypothesis claims that subjects may be willing to bid above their value to enjoy a positive utility gain from winning. Spite hypothesis proposes that subjects may want to increase the price above their value to spite the winner. Cooper and Fang (2008) study the relationship between bidders' perception of their opponent and overbidding, and found a positive correlation between the degree of overbids and the bidders' belief about opponent's value, consistent with the spite hypothesis. Andreoni, Che and Kim (2007) consider bidders who are partitioned into groups such that bidders' values are common knowledge within the group, and found evidence of the role of spite in overbidding. Our exit-survey result also indicates that the overbidding not driven by jump-bidding in our treatments is mainly induced by the spite incentive.[31]

A few papers in the literature investigate whether the overbidding observed in the lab is persistent. Kagel, Harstad, and Levin (1987) found that overbidding in English auc-

[31] Here are a few selected responses to the question "Suppose that your value is 10. Briefly describe your behavior in the auction" in our exit-survey.
"Wait until the price go[es] higher, maybe this is to prevent others [from] earn[ing] more."
"Since my value is quite small, I would want to have some risk. I should stay in the auction even the current value [price] exceed my value. I would quit the auction when the current value [price] reaches 15. As 15 is still a small number, I would assume that the opponent is having a value bigger than 15. But as I quit after the current value [price] exceed my value, the opponent is going to earn less."
"10 is small number, which almost has no chance to win the auction, so what I am going to do is to minimize my opponent's gain. Usually I will wait until the clock reaches about 18-20 and opt out the auction because in this case there is over 80% chance that my opponent will have a larger value, so I will bet he/she has a value not smaller than 25."

Figure 8: Z-tree Screen Shot - *Binary-II* Treatment



tions is a short-term phenomenon that subjects quickly learn not to undertake.[32] With the subjects who are MBA / senior undergraduate students, overbidding disappeared after a few (6-7) rounds out of 30 rounds. More recently, Garratt, Walker and Wooders (2012) study the bidding behavior of highly experienced participants in eBay auctions. They found that subjects with substantial prior experience exhibited no greater tendency to overbid than to underbid and, as a result, auction revenue was not significantly different from the hypothetical revenue.

We design two new treatments, *Binary-II* and *No-jump-II* parallel to *Binary* and *No-jump* treatments, with an additional experimental control. Two sessions for each treatment with 20 subjects for each session were conducted. Recall that in our treatments we randomly selected one round (out of 10) to calculate the final payment for each subject. In the new design, which we name as the *Amended Random Payment* (*ARP*) design, we inform each individual if the current round is the payment round for his/her opponent or not (See Figure 8). Throughout the auction, however, each individual never knows if the current round is the payment round for him/herself. This new design aims at fully controlling or discarding any kind of other-regarding preferences that may affect subjects' bidding behaviors.[33] We also revised the experimental instructions carefully, re-

[32]Note that our way to implement the English auction relying on the "clock" implementation was inspired by the experimental design in Kagel, Harstad, and Levin (1987).

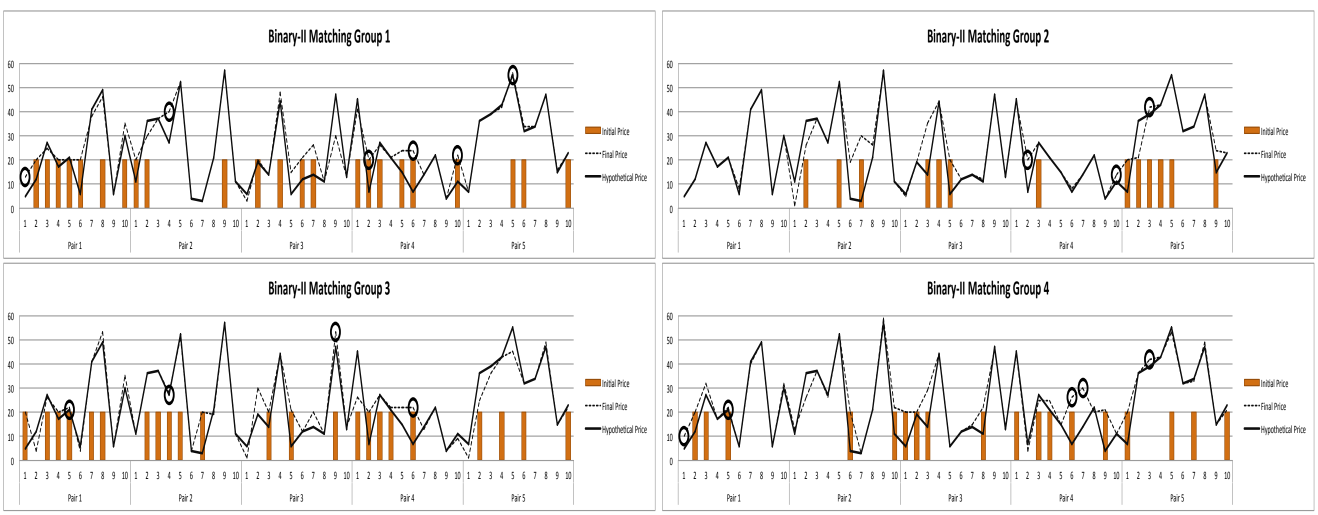
[33]There are a few other possible ways to control the other-regarding preferences in the literature. As implied by Kagel, Harstad, and Levin (1987) and Garratt, Walker and Wooders (2012), one can consider a longer time horizon or inviting more experienced subjects. Or one can design a game such that a subject plays against a fictitious player such as a robot playing a particular strategy or against prior human players

placing any words that potentially provoke joy of winning and/or spitefulness (such as win/lose, and opponent) with more neutral terms.

6.1 Bidding Behavior

Figures 9 and 10 present the experimental data from the two treatments. Tables 5, 6, and 7 report summaries of bidding frequencies from all data, data from the opponent's payment rounds, and data from opponent's no-payment rounds. Overall, the outcome from the new treatments is qualitatively the same as the outcome from the treatments in the previous section. One noticeable difference is that overbidding is observed significantly less frequently in *No-jump-II* treatment than in *No-jump* treatment (8.25 vs. 18.5 on average, one-sided KS test, $p = 0.008$).

Figure 9: Bidding Behaviors - *Binary-II* Treatment

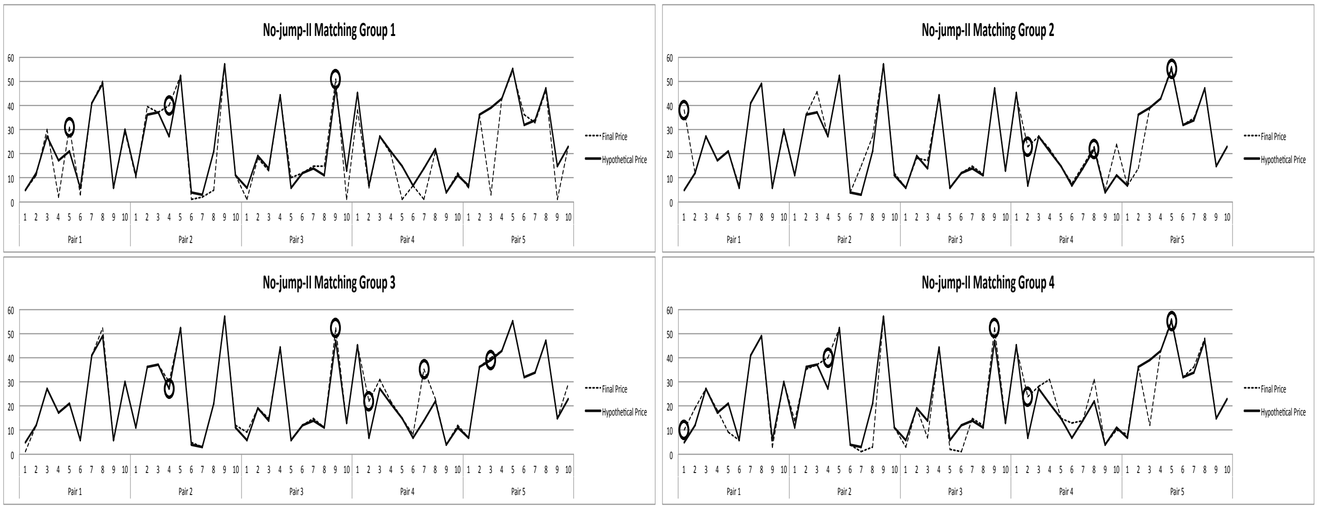


Note: The solid ovals indicate that overbidding is observed when the current round is the opponent's payment round.

It would be useful to focus on the data from the opponent's payment rounds presented in Table 6 to understand the relationship between the overbidding and the spite

(e.g. Johnson, Camerer, Sen, and Rymon, 2002; Cason and Sharma, 2007). We believe that our *CUP* method may have some advantages. First, it provides a way to get rid of other-regarding preferences of human subjects without relying on the fictitious player. Second, it allows us to make a direct comparison between data with and without the concerns of other-regarding preferences for the same set of human subjects. Third, our method is very simple to implement and can be applied to a broader range of games. Fourth, our method is less restrictive to some practical issues such as inviting human subjects who fulfil certain conditions (e.g. experiences) and keeping the length of a session reasonablly short.

Figure 10: Bidding Behaviors - *No-jump-II* Treatment



Note: The solid ovals indicate that overbidding is observed when the current round is the opponent's payment round.

Table 5: Bidding Frequencies - All Data

		Binary-II					*No-jump-II*				
Matching Group		1	2	3	4	Mean	1	2	3	4	Mean
FP = HP (±1)		27	36	26	26	28.75 (33)	31	42	41	31	36.25 (29.5)
OB	JB Direct	6	2	6	5	4.75 (3.75)			N/A		
	JB Indirect	7	4	3	6	5 (3.25)					
	No-Jump	3	5	5	7	5 (8.25)	8	7	8	10	8.25 (18.5)
UB	JB Direct	0	2	2	1	1.25 (0.5)			N/A		
	JB Indirect	4	1	2	2	2.25 (0.25)					
	No-Jump	3	0	6	3	3 (1)	11	1	1	9	5.5 (2)

Note: Numbers inside brackets are corresponding values from Binary and No-jump Treatments.

Table 6: Bidding Frequencies - Payment Rounds

		Binary-II					*No-jump-II*				
Matching Group		1	2	3	4	Mean	1	2	3	4	Mean
FP = HP (±1)		4	6	4	4	4.5	4	8	5	3	5
OB	JB Direct	1	0	2	0	0.75			N/A		
	Else (Spite)	4	4	2	4	3.5	3	2	4	5	3.5
UB	JB Direct	0	0	0	0	0			N/A		
	Else (Spite)	1	0	2	2	1.25	3	0	1	2	1.5
Total		10	10	10	10	10	10	10	10	10	10

Table 7: Bidding Frequencies - No-payment Rounds

		Binary-II					*No-jump-II*				
Matching Group		1	2	3	4	Mean	1	2	3	4	Mean
FP = HP (± 1)		23	30	22	22	24.25	27	34	36	28	31.25
OB	JB Direct	5	2	4	5	4			N/A		
	JB Indirect	5	2	1	5	3.25					
	Else	1	3	5	4	3.25	5	5	4	5	4.75
UB	JB Direct	0	2	2	1	1.25			N/A		
	JB Indirect	4	1	2	1	2					
	Else	2	0	4	2	2	8	1	0	7	4
Total		40	40	40	40	40	40	40	40	40	40

incentive. Two features are emerging from the data. First, a significant degree of overbidding has been observed in both treatments. For each matching group, there are 8 rounds in which a spite opportunity exists where the subject with a lower value is informed that the current round is the payment round of the opponent, and subjects indeed executed it (3.5 times on average in both treatments). The same information can be found in Figures 9 and 10 where the solid ovals highlight the instances in which the final price is strictly higher than the hypothetical price when the current round is the payment round of the opponent.[34] Second, there is no statistical difference in the bidding behaviors conditional on the current round being the payment round of the opponent in the two treatments. Two-sided KS test reveals that the frequency of overbidding not driven by jump-bidding in *Binary-II* is statistically not different from the frequency of overbidding in *No-jump-II* treatment (with $p = 1.00$). Similarly, the frequency of underbidding not driven by jump-bidding in *Binary-II* is statistically not different from the frequency of underbidding in *No-jump-II* treatment (with $p = 1.00$). This observation suggests that our *ARP* design allows us to identify the spite-driven overbidding and to successfully separate it from the jump-driven overbidding.

Now focus on the data from the opponent's no-payment rounds presented in Table 7. Admittedly, overbidding and underbidding led by mistakes and misunderstanding

[34]In total, there are 18 and 17 solid ovals respectively in Figures 9 and 10 indicating that the average frequency of overbidding induced by the spite incentive is 4.5 and 4.25 in the two treatments. 4 such observations in *Binary-II* and 3 in *No-jump-II* treatment have the final price just one unit higher than the hypothetical price and thus are not included in the overbidding category so that the reported average frequencies in Table 6 turn out to be 3.5 for both treatment.

are still unavoidable.[35] However, such over/underbidding behaviors seem to be well-controlled as no significant difference in the frequency of over/underbidding exists (two-sided KS test, $p = 0.368$) between the two treatments. Hence, the only qualitative difference between the two treatments in terms of the bidding behaviors conditional on the current round being one of the no-payment rounds of the opponent is the presence/absence of the over/underbidding directly and indirectly induced by jump-bidding.

Result 4. *1) In Binary-II treatment, jump-bidding directly and indirectly induces not only overbidding but also underbidding with a higher frequency of overbidding induced than underbidding. 2) A non-negligible degree of overbidding not driven by jump-bidding is observed in both Binary-II and No-jump-II treatments with no statistical difference.*

6.2 Revenue Analysis

Table 8: Revenue Decomposition - All Data

		Overbidding			Underbidding			
Binary-II	*Hypothetical*	JB Direct	JB Indirect	No-jump	JB Direct	JB Indirect	No-jump	*Actual*
Matching Group 1	1,163	+48	+70	+31	-1	-16	-24	1,271
Matching Group 2	1,163	+27	+60	+40	0	-25	-12	1,253
Matching Group 3	1,163	+54	+43	+32	0	-33	-39	1,220
Matching Group 4	1,163	+52	+83	+34	0	-25	-12	1,306
Mean	1,163	+45.25	+64	+34.25	-0.25	-24.75	-21.75	1,262.5

No-jump-II	*Hypothetical*	Overbidding	Underbidding	*Actual*
Matching Group 1	1,163	+48	-151	1,060
Matching Group 2	1,163	+99	-25	1,237
Matching Group 3	1,163	+69	-4	1,228
Matching Group 4	1,163	+85	-90	1,158
Mean	1,163	+75.25	-67.5	1,170.75

Tables 8 and 9 report the revenue decomposition result based on all data and based

[35] Our exit-survey result reveals that overbidding was made by mistake or by misunderstanding of some subjects who believed that they can still spite their opponent even in the no-payment round. Regarding underbidding, there were three individuals who reported that they gave up (and bid 0) whenever their value is smaller than a certain level.

Table 9: Revenue Decomposition - No-payment Rounds

		Overbidding			Underbidding			
Binary-II	*Hypothetical*	JB Direct	JB Indirect	No-jump	JB Direct	JB Indirect	No-jump	*Actual*
Matching Group 1	**929**	+35	+41	+9	0	-16	-7	991
Matching Group 2	**929**	+27	+48	+23	0	-25	-12	990
Matching Group 3	926	+26	+20	+32	0	-33	-25	946
Matching Group 4	926	+52	+63	+10	0	-6	-13	1,032
Mean	927.5	+35	+43	+18.5	0	-20	-14.25	989.75

No-jump-II	*Hypothetical*	Overbidding	Underbidding	*Actual*
Matching Group 1	926	+21	-86	861
Matching Group 2	926	+48	-25	949
Matching Group 3	926	+23	0	949
Matching Group 4	926	+38	-51	913
Mean	926	+32.5	-40.5	918

Note: Because of a programming mistake in the first session of *Binary-II* treatment, we had the payment round of one subject in each matching group different from that of other sessions. As a result, the hypothetical revenue in the matching group 1 and 2 of *Binary-II* treatment is 929, slightly higher than 926 in other sessions.

on the data from the opponent's no-payment rounds, respectively. Table 8 shows that jump-bidding contributes to the revenue significantly and positively. Consequently, the actual revenue from *Binary-II* treatment is bigger than that from *No-jump-II* treatment although the difference is not significant (one-sided KS test, $p = 0.105$). The amount of revenue increased by overbidding not driven by jump-bidding is larger in *No-jump-II* treatment than in *Binary-II* treatment (one-sided KS test, $p = 0.018$). At the same time, the amount of revenue decreased by underbidding not driven by jump-bidding is also larger in *No-jump-II* treatment than in *Binary-II* treatment although the difference is not statistically significant (one-sided KS test, $p = 0.105$) due to the high variance of the frequency particularly in *No-jump* treatment.

The result from the no-payment round data presented in Table 9 confirms and reinforces the main finding from the all data. Mann-Whitney U test reveals that the actual revenue from *Binary-II* treatment is significantly higher than the hypothetical revenue (one-sided, $p = 0.019$) and than the actual revenue from *No-jump-II* treatment (one-sided

$p = 0.081$). In the meantime, we cannot reject the null hypothesis that the actual revenue from *No-jump-II* treatment is not significantly different from the hypothetical revenue (two-sided, $p = 1.000$).

Result 5. *With the additional experimental control for the spite-driven overbidding, the actual revenue from No-jump-II treatment is not different from the hypothetical revenue while the actual revenue from Binary-II treatment is significantly higher not only than the hypothetical revenue but also than the actual revenue from No-jump-II treatment.*

7 Conclusion

Jump-bidding is frequently observed in real-life auctions. Although several papers (e.g., Avery [2] and Daniel and Hirshleifer [8]) have provided convincing analyses on this phenomenon, the previous researchers suggest that sellers' revenue decreases when jump-bidding occurs, a finding in sharp contrast to the fact that jump-bidding is allowed in real-life auctions (e.g., Sotheby's auctions and FCC spectrum auctions). In this paper, our auction experiments demonstrate that sellers' revenue increases significantly when jump-bidding occurs. Furthermore, our data show that bidding behavior and sellers' revenue are closely related to bidders' risk attitudes. We thus provide a theory of jump-bidding that is consistent with our experimental outcomes.

Finally, because we consider different settings than other researchers, we wish to emphasize that our results do *not* imply that the previous papers are incorrect.[36] Rather, the complete picture of jump-bidding has yet to be seen. Thus, this paper complements the previous studies by using experiments and a particular theory to identify the positive revenue effect of jump-bidding.

[36] For example, we adopt the IPV setup, whereas Avery [2] adopts the common-value setup; we consider risk-averse bidders, whereas Daniel and Hirshleifer [8] and Avery [2] consider risk-neutral bidders.

Appendix A – Figures and Tables

Table 10: Eliciting Risk Attitudes

Row No.	Option A Outcome $A1 = \$Y + h$	Outcome $A2 = \$Y - h$	Option B
1	Prob 35/100	Prob 65/100	Certain Outcome $\$Y$
2	Prob 40/100	Prob 60/100	
3	Prob 45/100	Prob 55/100	
4	Prob 50/100	Prob 50/100	
5	Prob 55/100	Prob 45/100	
6	Prob 60/100	Prob 40/100	
7	Prob 65/100	Prob 35/100	
8	Prob 70/100	Prob 30/100	
9	Prob 75/100	Prob 25/100	
10	Prob 80/100	Prob 20/100	
11	Prob 85/100	Prob 15/100	
12	Prob 90/100	Prob 10/100	

Figure 11: Average Frequency of Safe Choices (Option B)

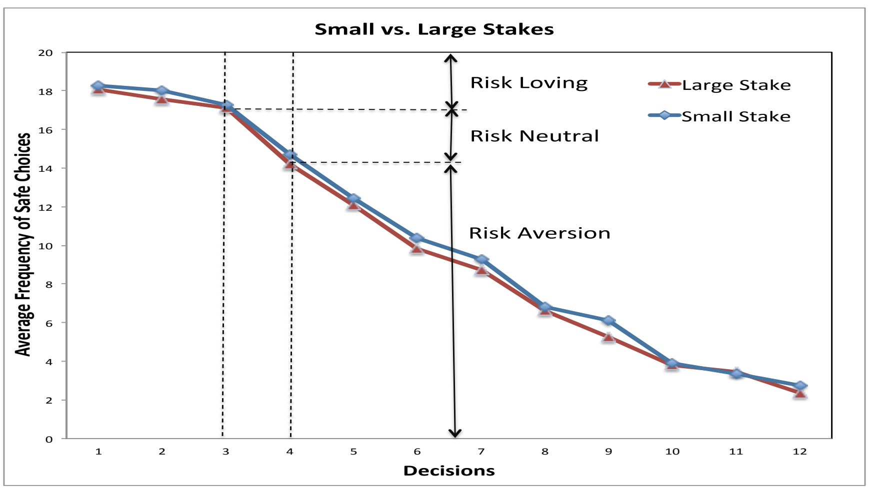


Table 11: Elicited risk attitudes - Individual Level

		risk aversion CARA	IARA	DARA	Risk-loving	Unclassified
Baseline	Session 1	5	4	5	3	3
	Session 2	11	4	2	1	2
Binary	Session 1	7	5	5	3	0
	Session 2	9	3	4	0	4
No-jump	Session 1	9	4	3	1	3
	Session 2	12	1	3	2	2
	Session 3	5	2	6	3	4
Binary-II	Session 1	10	4	5	0	1
	Session 2	5	5	4	2	4
No-jump-II	Session 1	9	2	1	5	3
	Session 2	8	3	5	1	3
Total		90	37	43	21	29

Note: CARA risk aversion includes the weak risk aversion, i.e. risk neutral.

Appendix B – Proofs

Proof of Proposition 2

By following (σ_1^*, σ_2^*), the high types (i.e., $v_i, v_{-i} \geqslant v^*$) jump to $k(v^*)$ in stage 1, and the low types (i.e., $v_i, v_{-i} < v^*$) do not jump. I.e., bidders use the jump bid $k(v^*)$ to signal their high values. In the case that $\beta_{-i} = k(v^*)$ and $v_i < v^*$, bidder i infers that $v_{-i} \geqslant v^*$ and expects no chance to win, and hence bidder i quits immediately. For all other cases, bidder i follows the weakly dominant strategy $b_i(\beta_i, \beta_{-i}, v_i) = \max\{\beta_i, \beta_{-i}, v_i\}$ in the clock auction in stage 2. Thus, (σ_1^*, σ_2^*) is a PBE if and only if the bidders' signalling is credible, i.e., the high types prefer "jumping to $k(v^*)$" and the low types prefer "no jump."[37] Define

$$N(v_i) := \int_0^{v_i} u(v_i - v_{-i}) dF(v_{-i}); \tag{2}$$

$$J(v_i) := F(v^*) u(v_i - k(v^*)) + \int_{v^*}^{\max\{v^*, v_i\}} u(v_i - v_{-i}) dF(v_{-i}); \tag{3}$$

where $N(v_i)$ and $J(v_i)$ are the expected utility of type v_i for "no jump" and "jumping to $k(v^*)$," respectively, given σ_{-i}^* chosen by bidder $-i$.

Lemma 1. *(σ_1^*, σ_2^*) is a PBE if and only if*

$$J(v_i) - N(v_i) \begin{cases} \leqslant 0 & \text{if } v_i < v^*; \\ \geqslant 0 & \text{if } v_i \geqslant v^*. \end{cases}$$

Proof of Proposition 2. Define

$$g(v_i) := u(v_i - k(v^*));$$

$$h(v_i) := E_{v_{-i} \sim [0, v^*] \text{ with cdf } \frac{F(v_{-i})}{F(v^*)}} [u(v_i - v_{-i})] = \int_0^{v^*} u(v_i - v_{-i}) d\frac{F(v_{-i})}{F(v^*)}.$$

[37] According to σ_{-i}^*, if bidder i jumps to any off-equilibrium price in stage 1, bidder $-i$ stays in the auction in stage 2 until the price reaches his true value. As a result, jump bidding is useless for bidder i and he prefers no jump to any off-equilibrium jump in stage 1.

By (2) and (3), we have

$$J(v_i) - N(v_i) = \begin{cases} F(v^*) \times [g(v_i) - h(v_i)] - \int_{v^*}^{v_i} u(v_i - v_{-i}) dF(v_{-i}) & \text{if } v_i < v^*; \\ F(v^*) \times [g(v_i) - h(v_i)] & \text{if } v_i \geqslant v^*, \end{cases}$$

which implies

$$J(v_i) - N(v_i) \begin{cases} \leqslant F(v^*) \times [g(v_i) - h(v_i)] & \text{if } v_i < v^*; \\ = F(v^*) \times [g(v_i) - h(v_i)] & \text{if } v_i \geqslant v^*, \end{cases} \tag{4}$$

because $\int_{v^*}^{v_i} u(v_i - v_{-i}) dF(v_{-i}) \geqslant 0$ for every $v_i < v^*$.

The properties of IARA and CARA (see Matthews [21], p. 638) imply

$$IARA: \; g(v_i) = h(v_i) \implies g'(v_i) > h'(v_i); \tag{5}$$

$$CARA: \; g(v_i) = h(v_i) \implies g'(v_i) = h'(v_i). \tag{6}$$

Note that (5) implies $g(\cdot)$ and $h(\cdot)$ cross at most once. In particular, $g(v^*) = h(v^*)$. Hence,

$$\text{given } IARA : g(v_i) - h(v_i) \begin{cases} < 0, & \text{if } v_i < v^*; \\ = 0, & \text{if } v_i = v^*; \\ > 0, & \text{if } v_i > v^*. \end{cases} ; \tag{7}$$

$$\text{given } CARA : g(v_i) - h(v_i) = 0, \forall v_i \in [0,1]. \tag{8}$$

(4), (7) and (8) imply

$$\text{given } IARA \text{ or } CARA : J(v_i) - N(v_i) \begin{cases} \leqslant 0 & \text{if } v_i < v^*; \\ \geqslant 0 & \text{if } v_i \geqslant v^*. \end{cases}$$

Therefore, (σ_1^*, σ_2^*) is a PBE by Lemma 1.■

Proof of Theorem 1

There are possible three events: i) $[v_i < v^* \leqslant v_{-i} \text{ with } i \in \{1,2\}]$, ii) $[\max\{v_1,\ v_2\} < v^*]$ and iii) $[v^* \leqslant \min\{v_1,\ v_2\}]$. In event ii) or iii), the seller gets the same revenue in both (σ_1^*, σ_2^*) and $(\widehat{\sigma}_1, \widehat{\sigma}_2)$. Conditional on event i), the expected revenues in (σ_1^*, σ_2^*) and $(\widehat{\sigma}_1, \widehat{\sigma}_2)$ are $k(v^*)$ and $\int_0^{v^*} v_i d\frac{F(v_i)}{F(v^*)}$, respectively. Given risk-averse bidders, $u(\cdot)$ is strictly concave and

$$u\left[v^* - \int_0^{v^*} v_i d\frac{F(v_i)}{F(v^*)}\right] = u\left[\int_0^{v^*} (v^* - v_i)\, d\frac{F(v_i)}{F(v^*)}\right] > \left[\int_0^{v^*} u\,(v^* - v_i)\, d\frac{F(v_i)}{F(v^*)}\right] = u(v^* - k(v^*)), \tag{9}$$

where the first equality follows from $\int_0^{v^*} d\frac{F(v_i)}{F(v^*)} = 1$; the inequality follows from Jensen's inequality; the last equality follows from the definition of $k(v^*)$ (see (1)). Thus, (9) implies

$$k(v^*) > \int_0^{v^*} v_i d\frac{F(v_i)}{F(v^*)}.$$

That is, the seller has more expected revenue in (σ_1^*, σ_2^*) than in $(\widehat{\sigma}_1, \widehat{\sigma}_2)$.■

Proof of Theorem 2

First, since (σ_1^*, σ_2^*) is a PBE, we have

$$Eu_i\left(v_i|\sigma_i^*, \sigma_{-i}^*\right) \geqslant Eu_i\left(v_i|\widehat{\sigma}_i, \sigma_{-i}^*\right),\ \forall v_i \in [0,1]. \tag{10}$$

Furthermore, $\left(\widehat{\sigma}_i, \sigma_{-i}^*\right)$ and $\left(\widehat{\sigma}_i, \widehat{\sigma}_{-i}\right)$ induce different outcomes if and only if $v_i \leqslant v^* \leqslant v_{-i}$ for some i. In particular, in such a case, bidder i loses in both $\left(\widehat{\sigma}_i, \sigma_{-i}^*\right)$ and $(\widehat{\sigma}_1, \widehat{\sigma}_2)$, i.e., $u_i\left(v_i|\widehat{\sigma}_{-i}, \sigma_{-i}^*\right) = u_i\left(v_i|\widehat{\sigma}_1, \widehat{\sigma}_2\right) = 0$ if $v_i \leqslant v^* \leqslant v_{-i}$. Hence,

$$Eu_i\left(v_i|\widehat{\sigma}_{-i}, \sigma_{-i}^*\right) = Eu_i\left(v_i|\widehat{\sigma}_i, \widehat{\sigma}_{-i}\right)\ \forall v_i \in [0,1]. \tag{11}$$

(10) and (11) imply $Eu_i\left(v_i|\sigma_i^*, \sigma_{-i}^*\right) \geqslant Eu_i\left(v_i|\widehat{\sigma}_i, \widehat{\sigma}_{-i}\right)$ for every $v_i \in [0,1]$.■

Appendix C – Experimental Instructions: *Baseline*

INSTRUCTION

Welcome to the experiment. This experiment studies decision making between two individuals. In the following hour or so, you will participate in 10 rounds of decision making. Please read the instructions below carefully; the cash payment you will receive at the end of the experiment depends on how you make your decisions according to these instructions. Communication of any kinds with any other participants will not be allowed.

Your Group

There are 20 participants in today's session. Prior to the first round, 20 people are equally and anonymously divided into 2 classes. Your class will remain fixed throughout the experiment. In each round you will be matched with another participant in your class to form a group of two. Participants will be randomly rematched after each round to form new groups, and each participant in your class have an equal chance to be matched with you. You will not be told the identity of the participant you are matched with, nor will that participant be told your identity—even after the end of the experiment.

Your Decision in Each Round

In your group, there are two individuals, yourself and your opponent. In each round and for each individual, the computer randomly and independently selects **Your Value** from 1 to 60. Each integer number between 1 and 60 has equal chance to be selected. At the beginning of each round, you will be informed about your value. You will not be told the value of the participant you are matched with, nor will that participant be told your value.

In each round, you are endowed with 60 tokens and are asked to **make a bid** to win an auction that consists of the following two stages: Initial Bidding Stage (Stage 1) and Price Clock Stage (Stag 2).

Stage 1: Initial Bidding Stage

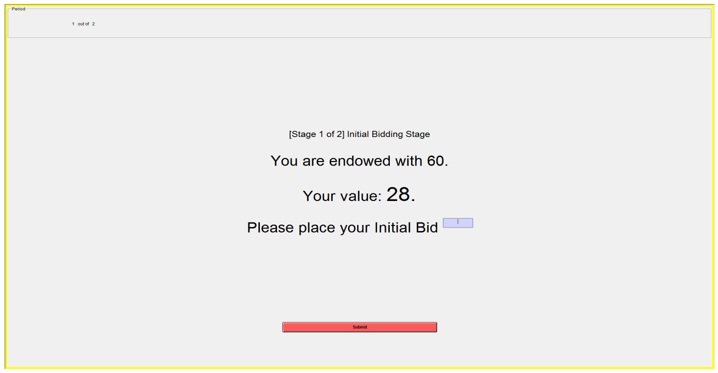
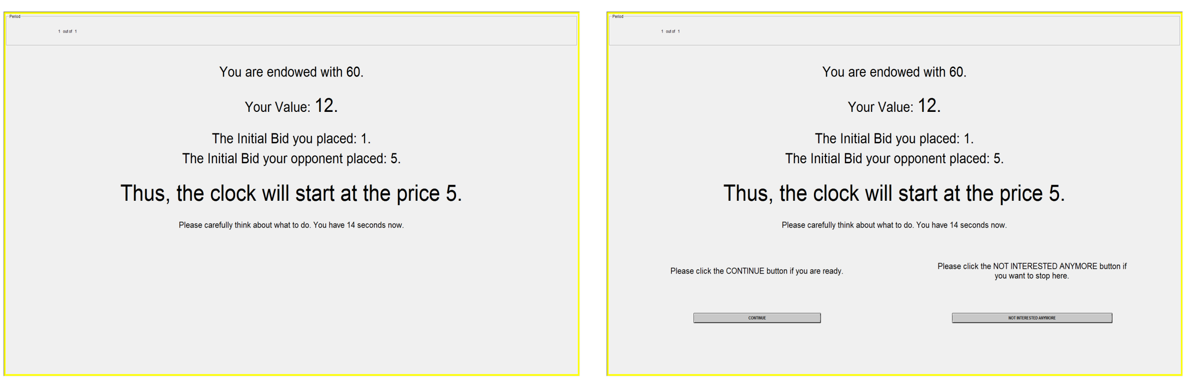


Figure 12: Stage 1 – Initial Bidding Stage

You will be informed about your value and be asked to place your **Initial Bid** (see Figure 12). The initial bid can be any integer number between 0 and 60, inclusively. Once you input your initial bid, you click the submit button. Note that the **maximum** of your initial bid and your opponent's initial bid will become the **Initial Price** in the next stage, which will be explained further below.

After you and your opponent click the submit button, you will be informed about the initial price as you see in Figure 13(a). You will be asked to think for a number of seconds on what to do next. The number of seconds you stay with the screen will be randomly determined between 5 seconds and 15 seconds. The waiting time is also independent upon your initial bids.



(a) Waiting Screen (b) Continue or Opt-out

Figure 13: Initial Price and Opt-out Decision

If you submit an initial bid strictly lower than your opponent's initial bid (which is equal to the initial price), you will be asked to decide whether to **continue** (by clicking the CONTINUE button) or to **opt out** (by clicking the NOT INTERESTED ANYMORE button). (See Figure 13(b) for the details). If you opt out, your opponent wins the auction with the initial price; if you continue, you will proceed to Stage 2.

If you submit an initial bid higher than or equal to your opponent's initial bid, you will be asked to click the CONTINUE button to proceed to Stage 2.

Stage 2: Price Clock Stage

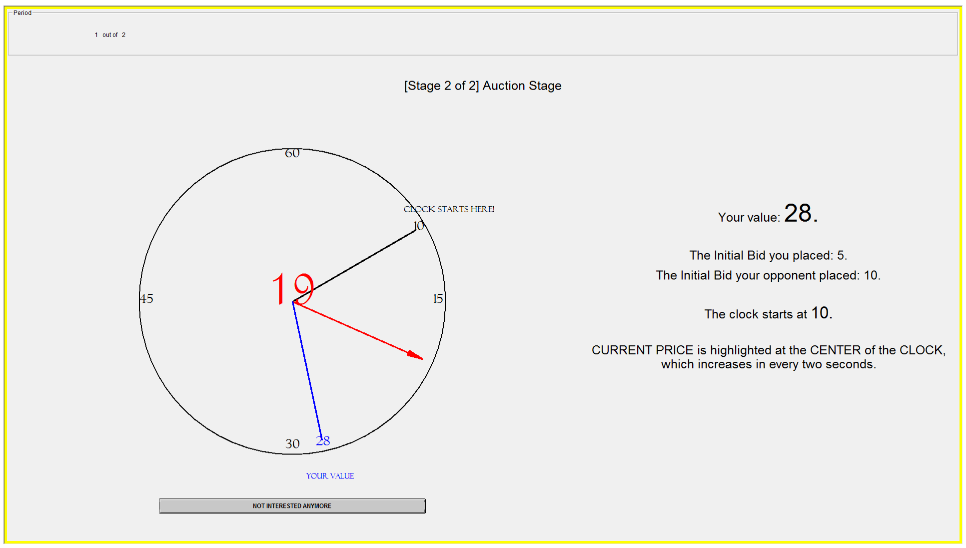


Figure 14: Stage 2 – Price Clock Stage

Figure 14 demonstrates an example of your decision screen in Stage 2. On the left-hand side of your screen, a **Price Clock** will be presented with three pieces of information on it: (1) Initial Price, (2) Current Price, and (3) Your Value.

(1) **Initial Price**: The price clock starts with the Initial Price determined in the Initial Bid Stage (= the maximum of the initial bids).

(2) **Current Price**: the current price is displayed at the center of the Clock (highlighted in **Red** colour). In every **two** seconds, the clock goes and the current price increases in 1 unit.

(3) **Your Value**: Your value is highlighted in the clock with **Blue** colour.

Under the price clock, a button "NOT INTERESTED ANYMORE" is in place. Whenever one of the individuals in your group clicks the button, the price clock stops and the auction ends.

The individual who stays in the auction is declared the winner, and pays the price showing on the clock. Once an individual has opted out, he/she cannot re-enter. If no one drops out until the current price becomes 60, the auction ends and the final price becomes 60. In this case, each individual has equal chance to win the auction.

Your Earning in Each Round

- If you do not win the auction, your earning becomes your endowment 60.
- If you win the auction, your earning becomes

$$\text{Endowment} + \text{Your Value} - \text{Final Price.}$$

  For example, when you win the auction with your value 28 and the final price 19, your earning in the round becomes $60 + 28 - 19 = 69$.

Information Feedback

At the end of each round, you will be informed about Your Value, Your Opponent's Value, Your Initial Bid, Your Opponent's Initial Bid, Final Price, Auction Outcome (win or lose) and Your Earning.

Your Cash Payment

The experimenter *randomly* selects 1 round to calculate your cash payment. (So it is in your best interest to take each round seriously). Your total cash payment at the end of the experiment will be the number of tokens you earned in the selected round (translated into HKD with the exchange rate of 1 Token = 1 HKD) plus a 30 HKD show-up fee.

Practice Rounds

To ensure your comprehension of the instructions, we will provide you with a practice round. Once the practice round is over, the computer will tell you "The official rounds begin now!"

Adminstration

Your decisions as well as your monetary payment will be kept confidential. Remember that you have to make your decisions entirely on your own; please do not discuss your decisions with any other participants.

Upon finishing the experiment, you will receive your cash payment. You will be asked to sign your name to acknowledge your receipt of the payment. You are then free to leave.

If you have any question, please raise your hand now. We will answer your question individually.

Appendix D – Instructions for Eliciting risk attitudes

INSTRUCTION- Bonus I

Please read the instructions carefully and make decisions. In the table below, there are 12 decisions to be made. Each row presents each decision. In each row, you need to choose one of two options, Option A and Option B.

- If you choose Option A, you will get either HKD 14 (Outcome A1) or HKD 6 (Outcome A2) depending on the realization of X on the Orange Card.
- X will be randomly drawn in the range between [1,100] inclusively. Each integer number in this range has an equal chance to be selected.
- If you choose Option B, you will get HKD 10 regardless of the realization of X on the Orange Card.
- Please make your decisions for all 12 rows and click SUBMIT / OPEN THE CARD button. Then, one row will be randomly selected and the selected row number will be presented on the Green Card. Each row has equal chance to be selected.
- Your earning in this bonus round will be determined by your decision for the selected row and the realization of X.

Please raise your hand if you have any questions.

Otherwise, please make your decision.

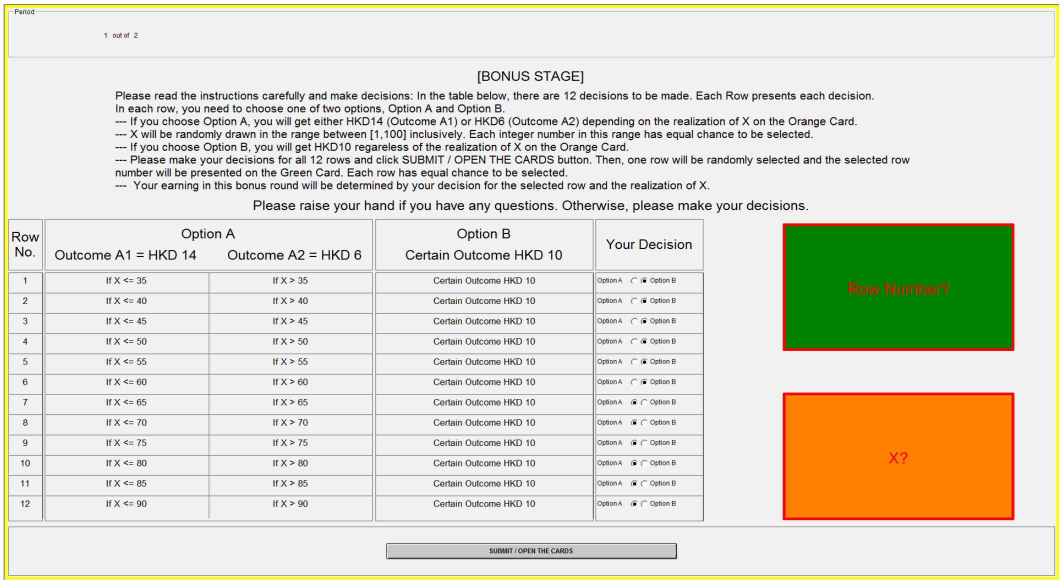


Figure 15: Z-tree Screen Shot - Bonus I

INSTRUCTION- Bonus II

In the table below, there are twelve decisions to be made.[38] Each row presents each decision.

Everything is the same as before except the followings:

- If you choose Option A, you will get either HKD 34 (Outcome A1) or HKD 26 (Outcome A2) depending on the realization of X on the Orange Card.
- If you choose Option B, you will get HKD 30 regardless of the realization of X on the Orange Card.

Please raise your hand if you have any questions.

Otherwise, please make your decision.

[38] Screen shot omitted. Note that the Bonus-II stage is unexpected for the subjects when they make decisions in the Bonus-I stage.

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