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ENTRY AND BIDDING BEHAVIOR IN SURPLUS-EXTRACTING AUCTIONS: AN EXPERIMENT

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Abstract

We provide experimental evidence on entry and bidding behavior in surplus-extracting auctions built on the second-price format. In addition to the simple second-price auction, we consider full- and partial-surplus-extracting auctions. The latter leaves more surplus to bidders under full entry than the former, while preserving the same set of undominated strategies: value bidding and opting out. In contrast to the second-price auction, both auctions exhibit lower entry and overbidding among entrants. Our findings highlight the interplay between entry and bidding behavior, shedding light on the trade-off between surplus extraction and strategic simplicity in auction design with voluntary participation.

Keywords: Auction experiment, Full surplus extraction, Second-price auction, Auction entry, Strategic uncertainty, Undominated strategies

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In his pioneering work, Vickrey (1961) established that the second-price auction is a simple mechanism in which bidding one's value is a dominant strategy.[1] Myerson (1981) subsequently demonstrated that the second-price auction with a reserve price can be optimal for the seller in environments with independent private values. By contrast, Crémer and McLean (1988) showed that statistical dependence among bidders' values can enable the seller to extract the full surplus through more sophisticated auctions. This *full-surplus-extraction* result has attracted considerable attention in mechanism design.

The key idea of Crémer and McLean (1988) is to condition each bidder's payment on opponents' bids, regardless of whether that bidder wins the item, so as to eliminate bidders' information rents. Despite this striking theoretical result, we are unaware of any real-world adoption of full-surplus-extracting auctions, and little is known about how bidders behave in such complex auctions.[2]

To clarify the sense in which these auctions are *complex* in strategic terms, consider a full-surplus-extracting mechanism proposed by Crémer and McLean (1988). This mechanism augments a second-price auction with a "lottery" whose realized prize or penalty depends solely on the opponents' bids. This feature immediately implies that value bidding is dominant for an entrant. Once the entry decision is taken into account, however, a bidder need not have a dominant strategy. In general, whether entry is optimal depends on the opponents' strategies, as their bids leave the entrant with an ex post loss through the lottery. Thus, although the bidding decision is strategically simple conditional on entry, the entire problem, including whether to enter, need not be.

The full-surplus-extraction result is more than a theoretical curiosity in auction theory. It has broader implications for the mechanism-design paradigm itself. In extending the (approximate) full-rent-extraction result to a general environment, McAfee and Reny (1992, p. 400) themselves argued that "the results (full rent extraction) cast doubt on the value of the current mechanism design paradigm as a model of institutional design."

[1] We use *(strategic) simplicity* in the classical sense that the relevant decision problem has a dominant strategy. Throughout the paper, all dominance relations are understood to be weak. See Li (2024) for a discussion of related notions of simplicity in mechanism design.

[2] Carroll (2019, p. 142), referring to a full-surplus-extracting auction, similarly notes, "It is fair to say that the auction described above is not one that we would see in practice."

As surveyed by Carroll (2019), one response to such concerns has been the development of robust mechanism design, which can provide a theoretical rationale for simple dominant-strategy mechanisms. In particular, Yamashita (2015) studied *robustness to strategic uncertainty*, motivated by settings such as anonymous online trading environments in which each agent may be unable to form accurate conjectures about others' strategies.[3] This approach assumes only that agents avoid dominated strategies, not that they play a Bayesian equilibrium, and evaluates each mechanism by its worst-case performance across undominated strategy profiles. He showed that a version of the second-price auction is worst-case optimal for the seller in an environment with private values.[4] Yamashita (2015) referred to this approach as "pessimistic." How conservative this criterion is in practice, however, is an empirical question—one that can be informed by evidence on how bidders actually behave in complex surplus-extracting auctions.

Against this background, we use a controlled experiment to investigate bidder behavior in surplus-extracting auctions based on the simple second-price format (Crémer and McLean 1988). We examine the extent to which subjects coordinate on equilibrium behavior and satisfy the weaker requirement of choosing undominated strategies. A central feature of our experimental design is that auction participation is voluntary. We view this feature as essential because any comprehensive assessment of strategically complex surplus-extracting auctions must account for entry decisions as well as bidding behavior. Referring specifically to full-surplus-extracting auctions, Milgrom (2004, p. 166) cautioned that "in real auctions, bidders frequently refuse to participate if the proposed mechanism seems strange or unfair." Our experiment examines this concern directly.[5]

Specifically, we design a between-subjects experiment in an environment with two bidders and correlated private values. Our main treatment is a full-surplus-extracting (FSE) auction, while a simple second-price (2P) auction serves as the benchmark. Be-

[3]Another strand of the literature has examined robustness to bidders' higher-order beliefs about values (Chung and Ely 2007; Chen and Li 2018; Yamashita and Zhu 2022; Pham and Yamashita 2024). This line of work falls within what Carroll (2019) referred to as robustness to structural uncertainty.

[4]Applying his general result, Yamashita (2015) also showed that this second-price auction is worst-case optimal in an environment with interdependent values.

[5]Nishimura (2022) conducted an experiment on surplus-extracting auctions in a simpler setting without an opt-out option. We discuss its relation to ours in the section on related literature.

cause FSE and 2P differ in both the extent of surplus extraction and strategic simplicity, comparing them alone would not distinguish the role of full surplus extraction from that of strategic complexity. We therefore introduce a second surplus-extracting treatment: a partial-surplus-extracting (PSE) auction. PSE shifts the FSE lottery payoffs upward by a constant whenever the opponent enters, thereby leaving bidders more surplus under full entry. The PSE treatment allows us to assess whether raising lottery payoffs in this way is sufficient to encourage entry. Like FSE, however, PSE remains strategically non-simple because neither value bidding nor opting out dominates the other.

A separate issue concerns bidding behavior conditional on entry. Experimental subjects may fail to recognize the dominance of value bidding conditional on entry and consequently choose dominated strategies. This concern is well founded: overbidding—bidding above one's value—is well documented in experiments on simple second-price auctions (Kagel and Levin 2016). More generally, dominated choices have been documented across a variety of experimental settings, and limitations in contingent thinking can be one contributing factor (Niederle and Vespa 2023).[6] If left unaddressed, such dominated overbidding could make it difficult to distinguish responses to surplus extraction from more general failures to recognize dominance relations.

In this regard, value bidding is substantially more common in dynamic ascending-clock auctions than in static second-price auctions (Kagel, Harstad and Levin 1987; Harstad 2000; Li 2017). Li (2017) explained this difference using the concept of obvious dominance, which can be recognized without contingent reasoning and is stronger than standard dominance. In our setting with voluntary participation, however, even a dominant-strategy mechanism must leave positive information rents to some bidders and therefore cannot achieve full surplus extraction.[7]

Since we cannot make the entire decision problem strategically simple, we instead use feedback to help subjects recognize the dominance of value bidding conditional on

[6]Relatedly, Park (2025) provided experimental evidence that failures in contingent reasoning become more frequent when a decision problem lacks a dominant choice.

[7]More generally, in a private-values auction environment with full support, full surplus extraction is incompatible with dominant-strategy incentive compatibility and ex post individual rationality; this follows from the standard characterization of ex post payoffs (see, e.g., Vohra 2011).

entry. To this end, we use the *ascending-clock presentation* developed by Breitmoser and Schweighofer-Kodritsch (2022). Under this scheme, bidders first submit sealed bids and then watch an ascending-price clock resolve the auction, with their submitted bids serving as automatic exit prices. Breitmoser and Schweighofer-Kodritsch (2022) provided experimental evidence that the clock presentation substantially reduces absolute deviations from value bidding in static second-price auctions. We therefore use the same sealed-bid format followed by this clock presentation in all three treatments.

Our experimental results reveal several behavioral differences across treatments. Entry is somewhat more frequent in PSE than in FSE but remains far below full entry in both. Initially, underbidding is common in all three treatments, but overbidding is already more prevalent in the surplus-extracting treatments than in 2P. In 2P, underbidding declines and value bidding becomes increasingly prevalent. In FSE and PSE, underbidding also declines, while overbidding becomes increasingly common.

A key feature for understanding low entry in the surplus-extracting treatments is the way lottery payoffs depend on the opponent's bid. In both FSE and PSE, when the opponent submits a sufficiently high bid, the lottery payoff becomes negative and can make entry unprofitable. Consistent with this feature, higher bids by recent opponents are associated with lower current entry in both treatments. In the early rounds, higher bids by recent opponents are also associated with higher bids relative to value among entrants. By contrast, in the simple 2P treatment with no lottery, recent opponent behavior is associated with neither entry nor bidding behavior among entrants.

Taken together, these findings show that subjects exhibit broadly similar behavioral patterns in the two surplus-extracting auctions, while behavior in both auctions differs markedly from that in the simple 2P auction. In particular, low entry is not confined to FSE: the entry rate in PSE remains substantially below even the lowest symmetric equilibrium benchmark. A plausible explanation is that systematic overbidding by some entrants may reduce entry incentives for other bidders. Moreover, seller revenue is zero whenever at least one bidder opts out, so lower entry can directly reduce revenue. One contribution of this study is to provide experimental evidence on the interplay between entry and bidding behavior, thereby shedding light on the trade-off between surplus extraction and strategic simplicity in auction design with voluntary participation.

A. Related literature

Building on an example in Myerson (1981), Crémer and McLean (1988) constructed auction mechanisms that extract the full surplus from risk-neutral bidders in environments with statistically dependent private values. They proposed two implementations, based respectively on dominant-strategy incentive compatibility and Bayesian incentive compatibility. Our experiment adopts the former, simpler implementation based on the second-price auction. Unlike the latter, it makes value bidding a dominant strategy conditional on entry. However, Crémer and McLean (1988) also noted that surplus-extracting auctions can admit equilibria other than the truth-telling equilibrium. This multiplicity may make coordination on the truth-telling equilibrium more difficult.

Two requirements for the full-surplus-extraction result are particularly relevant here: bidders follow the truth-telling equilibrium with full entry, and the joint prior distribution of values is common knowledge.[8] Yamashita (2015) relaxed the assumption of equilibrium play and showed that, given a prior over agents' private values, a version of the simple second-price auction maximizes the seller's worst-case expected revenue over undominated strategy profiles. Our experimental findings speak to the behavioral premise underlying Yamashita's approach: agents choose only undominated strategies, although they need not play an equilibrium.[9]

A complementary line of research relaxed the assumption that agents' beliefs about values are common knowledge. Chung and Ely (2007) allowed the seller to be uncertain about bidders' higher-order beliefs over values. They identified a belief structure under which a dominant-strategy auction maximizes expected revenue among all mechanisms

[8] A large theoretical literature has identified several obstacles and limitations to full surplus extraction. These include bidders' risk aversion and limited liability (Robert 1991), collusion among agents (Laffont and Martimort 2000), competition among sellers (Peters 2001), information acquisition about other bidders' types (Bikhchandani 2010), and the seller's limited knowledge of the joint value distribution (He and Li 2022).

[9] The role of undominated strategies has been studied in the literature on implementation theory since Börgers (1991) and Jackson (1992). For more recent work, see, among others, Carroll (2014), Mukherjee et al. (2019), and Mukherjee, Muto and Sen (2024).

that are Bayesian incentive compatible and interim individually rational, thereby providing foundations for simple dominant-strategy mechanisms.[10] Pham and Yamashita (2024) extended this foundation by showing that the result continues to hold even when the seller's and bidders' priors about values are heterogeneous but known to be arbitrarily close under an appropriate notion of distance. As shown by Pham and Yamashita (2024), a (perturbed) full-surplus-extracting mechanism designed under the seller's prior need not induce a truth-telling equilibrium with full entry when bidders hold nearby but heterogeneous priors.

Our experimental design is intended to make the value distribution as close to common knowledge as possible. Subjects are shown the joint prior distribution of values and, after observing their own value, the corresponding conditional distribution of the opponent's value. The design thus tightly controls beliefs about values while leaving subjects uncertain about others' behavior.

In a related experimental study, Nishimura (2022) compared bidding behavior under the two auction mechanisms proposed by Crémer and McLean (1988). That experiment, however, did not allow bidders to opt out. Our experiment allows bidders to opt out and examines how entry decisions interact with bidding behavior conditional on entry, focusing on the surplus-extracting auctions based on the simple second-price format.

A large body of experimental work has documented overbidding behavior in simple second-price auctions, both in environments with correlated private values (Kagel, Harstad and Levin 1987; Harstad 2000; Garratt, Walker and Wooders 2012; Li 2017; Breitmoser and Schweighofer-Kodritsch 2022) and in those with independent private values (Kagel and Levin 1993; Aseff 2004; Andreoni, Che and Kim 2007; Bartling and Netzer 2016; Georganas, Levin and McGee 2017; Schneider and Porter 2020; Tan 2020; Giebe et al. 2024). Researchers have attributed overbidding to several factors, including cognitive limitations in contingent reasoning (Li 2017), spite (Morgan, Steiglitz and Reis 2003), and the joy of winning (Cooper and Fang 2008).

[10] Chen and Li (2018) and Yamashita and Zhu (2022) generalized this result in several directions. Lopomo, Rigotti and Shannon (2022) studied robustness to the designer's uncertainty about agents' beliefs and derived necessary and sufficient conditions for full surplus extraction in their setting.

To mitigate the effects of potential limitations in contingent reasoning, our experimental design draws heavily on Breitmoser and Schweighofer-Kodritsch (2022). They showed that adding the ascending-clock presentation to a static second-price auction substantially reduced absolute deviations from value bidding and accounted for a large share of the reduction achieved by using a dynamic ascending-clock auction.

To address the concern that social preferences, including spite, may affect bidder behavior, we also employ the amended random-payment scheme developed by Lim and Xiong (2021) and Lafky, Lai and Lim (2022). Under this scheme, subjects are informed whether the current round is payoff relevant for their opponent, whereas their own payment round is revealed only at the end of the session. The scheme is intended to concentrate other-regarding behavior in opponents' payment rounds and thereby attenuate its influence in the other rounds. Consistent with this logic, we find that absolute deviations from value bidding conditional on entry decrease markedly when the opponent is unpaid.

Finally, our study relates to the experimental literature on endogenous entry into auctions. Particularly relevant is Aycinena and Rentschler (2018), who examined entry and bidding behavior in first-price and English clock auctions. In their experiment, bidders decide whether to enter after observing their values and a common opportunity cost of entry. They documented over-entry relative to risk-neutral equilibrium predictions in all treatments.[11] Our experiment differs in that the lottery payoff associated with entry depends on the opponent's behavior and is therefore strategically uncertain, whereas their entry cost was exogenously specified and known when deciding whether to enter. In contrast to their results, we observe entry below even the lowest risk-neutral symmetric equilibrium benchmark in PSE and, in the later rounds, in FSE as well.

The rest of the paper is organized as follows. Section I presents the theoretical benchmarks. Section II describes our experimental design. Section III contains the results. Section IV concludes. Appendix provides proofs. The Online Supplemental Material (OSM) contains additional material, including English translations of the experimental instructions.

[11] In a related experiment, Aycinena, Bejarano and Rentschler (2018) likewise document over-entry relative to risk-neutral predictions. See Aycinena and Rentschler (2018, p. 939) for additional references.

I. Model

A. Setup

Two risk-neutral bidders compete for a single item auctioned by the seller. Each bidder i has a value $v_i \in V := \{100, 200, ..., 10000\}$ for this item. We consider a tractable distribution over values given by the following mixture: with probability $\rho \in (0, 1)$, both bidders receive a common value drawn uniformly from V; with probability $1 - \rho$, their values are drawn independently and uniformly from V.[12] Thus, the bidders' values are positively correlated, with correlation coefficient ρ. We set $\rho = 1/3$ in the experiment and discuss the rationale for this parameter choice later in this subsection.

The bid space is $B := V \cup \{0\}$. Any positive bid $b_i \in V$ implies entry, whereas the null bid $b_i = 0$ represents opting out. We thus model opting out as one of the available bids, following Yamashita (2015). This opt-out option corresponds to the interim individual rationality constraint in Crémer and McLean (1988).

The three auctions $\tau \in \{\text{FSE}, \text{PSE}, \text{2P}\}$ introduced above are all based on the simple 2P format. Each game proceeds as follows. First, values (v_1, v_2) are realized, and each bidder i privately observes v_i. Second, the bidders submit sealed bids $b_i \in B$. Third, if $b_i > b_j$, then bidder i wins the item and pays the auction price, which equals the second-highest bid b_j. If $b_1 = b_2 > 0$, each bidder wins the item with equal probability and pays the tied bid. Finally, bidder i's realized profit is

$$\begin{cases} l_\tau(b_j) + v_i - b_j & \text{if bidder } i \text{ enters and wins,} \\ l_\tau(b_j) & \text{if bidder } i \text{ enters but loses,} \\ 0 & \text{if bidder } i \text{ opts out,} \end{cases}$$

where l_τ is a *lottery function* defined below. The seller's revenue is the auction price minus the lottery payoffs to the bidders.

Thus, conditional on entry, bidder i always receives the lottery payoff $l_\tau(b_j)$, which

[12] Carroll (2019) also uses a similar mixture distribution to illustrate full surplus extraction.

depends only on the opponent's bid b_j.[13] From an interim perspective, the lottery payoff is uncertain because the opponent's bid is not yet known.

The matrix of conditional distributions of the opponent's value satisfies the full-rank condition in Crémer and McLean (1988, Theorem 1). Hence, the seller can extract the full surplus by augmenting the 2P auction with a lottery l. Given the 2P format, the full-surplus-extracting lottery is uniquely determined by the joint prior distribution.[14] For our choice of the correlation parameter $\rho = 1/3$, the lottery payoff to bidder i is

$$l(b_j) = 2222 - \frac{b_j}{100}\left(\frac{b_j}{100} - 1\right), \qquad b_j \in V. \tag{1}$$

A key feature of the lottery function is that it is decreasing in the opponent's bid. The lottery payoff is positive when the opponent's bid is low and negative when it is high.

Using the lottery l, we define the lottery function $l_\tau : B \to \mathbb{R}$ for each auction treatment as follows:

$$l_\tau(b_j) := \begin{cases} l(b_j) + 1 & \text{if } \tau = \text{FSE}, \\ l(b_j) + 991 & \text{if } \tau = \text{PSE}, \\ 0 & \text{if } \tau = \text{2P}, \end{cases} \qquad b_j \in V, \tag{2}$$

and set $l_\tau(0) := 0$; that is, the lottery payoff is zero if the opponent opts out. The lottery l_{FSE} extracts nearly the full surplus. We add one to the original lottery to give strict entry incentives in equilibrium. The lottery l_{PSE} leaves more surplus to the bidders in equilibrium. The constant 991 is chosen so that the seller's ex ante expected revenue is approximately equal to that from the 2P auction with the optimal reserve price.[15] Importantly, the PSE lottery payoff remains negative when the opponent submits a sufficiently high bid. Finally, the null lottery l_{2P} yields the simple 2P auction.

[13] Following Crémer and McLean (1988), we use the term "lottery," although its payoff is deterministic given the opponent's bid.

[14] For general ρ, the lottery function is characterized by Lemma A1 in Appendix.

[15] The PSE auction yields an ex ante expected revenue of 4179, whereas the 2P auction with the optimal reserve price of 3800 yields an ex ante expected revenue of 4178.

Choice of the correlation parameter. As noted above, the correlation parameter ρ uniquely determines the full-surplus-extracting lottery l (Lemma A1). As ρ increases toward one and the joint value distribution approaches perfect correlation, l converges to the null lottery, making the resulting auction increasingly similar to the simple 2P auction. Conversely, as ρ decreases toward zero and the distribution approaches independence, the lottery entails increasingly extreme prizes and penalties. We therefore chose $\rho = 1/3$ as an intermediate value that generates a nontrivial lottery while avoiding excessively extreme lottery payoffs.

Outcome with a single entrant. In our setting, if only one bidder enters, then the entrant obtains the item at no cost because the opponent's bid, and hence the second-highest bid, is zero. An alternative formulation would specify no trade whenever either bidder opts out. Under that formulation, however, there would be a Bayesian Nash equilibrium in which both bidders always opt out, because unilateral entry would not result in trade and would yield a payoff of zero.

B. Theoretical benchmarks

To provide benchmarks for our experimental evaluation of the surplus-extracting auctions, we characterize the undominated bids and identify several Bayesian Nash equilibria in the three auctions.

Undominated bids. In line with Yamashita (2015), we first characterize the undominated bids. In any auction, a bid $b \in B$ is *undominated* for value $v \in V$ if, for a bidder with v, no other bid $b' \in B$ dominates the bid b.[16] The following proposition shows that, unlike in 2P, opting out remains undominated for every value in FSE and PSE.

Proposition 1. *For every $v \in V$, the unique undominated bid in 2P is $b = v$, whereas in both FSE and PSE, the set of undominated bids consists of $b = v$ and $b = 0$.*

[16] Specifically, for bidder i with value v, b_i' *dominates* b_i if $u(b_i', b_j; v) \geq u(b_i, b_j; v)$ for every $b_j \in B$, with strict inequality for some $b_j \in B$, where $u(b_i, b_j; v)$ denotes bidder i's ex post expected profit given bids b_i and b_j. A bid is *dominant* if it dominates any other bid. Yamashita (2015) calls an undominated message admissible.

All three auctions are Vickrey–Clarke–Groves mechanisms (Milgrom 2004) when the bid space is restricted to V. Hence, value bidding is dominant conditional on entry.[17] In 2P, value bidding also dominates opting out and is therefore dominant on the entire bid space B. The key feature of FSE and PSE underlying Proposition 1 is that the lottery functions are decreasing on V: when the opponent submits a sufficiently high bid, the resulting lottery payoff makes the bidder's ex post profit from value bidding negative, so opting out is preferred. Thus, neither value bidding nor opting out dominates the other.

Equilibria. As noted by Crémer and McLean (1988), surplus-extracting auctions can admit multiple equilibria. Since the bidders are ex ante symmetric, we focus on symmetric Bayesian Nash equilibria, allowing for behavioral strategies. We refer to any such symmetric equilibrium as an *equilibrium* unless otherwise stated.

In any symmetric equilibrium, a bidder with value v bids $b = v$ conditional on entry.[18] It follows that any symmetric equilibrium can be represented by an *entry strategy* $y : V \to [0, 1]$, under which a bidder with value v enters by bidding $b = v$ with probability $y(v)$ and opts out by choosing $b = 0$ with probability $1 - y(v)$.

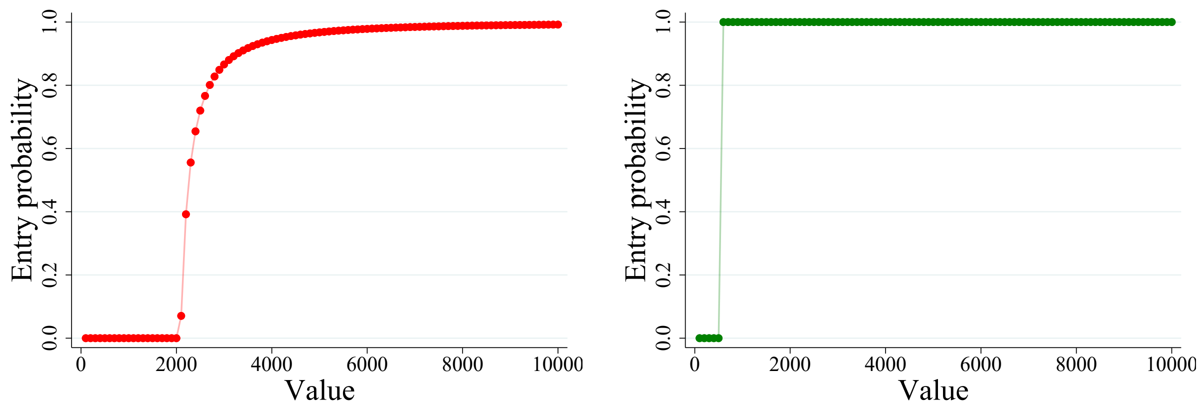
The canonical equilibrium prediction is full entry and value bidding (Vickrey 1961; Crémer and McLean 1988). Accordingly, all three auctions admit what we call the *full-entry (FE) equilibrium*, in which both bidders always enter and bid their values. This is the unique symmetric equilibrium of the 2P auction. Thus, in each auction, any symmetric equilibrium assigns zero probability to dominated bids.

The FSE and PSE auctions, however, also admit symmetric equilibria with partial entry. To obtain the opposite polar benchmark, we define the *minimum-entry (ME) equilibrium* as an equilibrium entry strategy y such that $y(v) \le y'(v)$ for every equilibrium entry strategy y' and every $v \in V$. Together, the FE and ME equilibria bound the range of entry rates that can be supported in symmetric equilibria. The ME equilibrium is not intended as an equilibrium-selection criterion; rather, it provides a benchmark for how much opting out can be rationalized by symmetric equilibrium behavior.

[17] For completeness, it is stated as Lemma A2 in Appendix.
[18] Lemma A3 in Appendix provides a proof.

Proposition 2. *The FSE and PSE auctions each have a unique ME equilibrium. In both auctions, the ME entry strategy y is nondecreasing in value. The ME entry strategy y in FSE has a threshold $v_\mathrm{F} \in V$ with $v_\mathrm{F} > l_\mathrm{FSE}(v_\mathrm{F})$ such that $y(v) = 0$ for every $v < v_\mathrm{F}$ and $y(v) \in (0, 1)$ for every $v \geq v_\mathrm{F}$. The ME entry strategy y in PSE has a threshold $v_\mathrm{P} \in V$ with $v_\mathrm{P} < l_\mathrm{PSE}(v_\mathrm{P})$ such that $y(v) = 0$ for every $v < v_\mathrm{P}$ and $y(v) = 1$ for every $v \geq v_\mathrm{P}$.*

Figure 1 illustrates the unique ME equilibrium for each auction. The ME equilibrium in FSE involves stochastic entry for values $v \geq v_\mathrm{F} = 2100$.[19] The ME equilibrium in PSE is given by a deterministic entry strategy with a threshold at $v_\mathrm{P} = 600$.



(a) ME entry strategy in FSE

(b) ME entry strategy in PSE

Figure 1: Minimum-entry equilibria.

Table 1 summarizes the ex ante equilibrium outcomes.[20] Consistent with the higher lottery payoffs, the ME entry probability in PSE is higher than in FSE. These outcomes provide benchmarks for comparison with the experimental results reported below.

Table 1: Ex ante equilibrium outcomes.

Auction	FSE		PSE		2P
Equilibrium	FE	ME	FE	ME	FE
Bidder's entry probability	1.00	0.74	1.00	0.95	1.00
Seller's revenue	6159	5968	4179	4456	3939
Profit per bidder	1	0	991	849	1111
Social surplus	6161	5968	6161	6155	6161

[19] Levin and Smith (1994) also show that auction entry can involve mixing in symmetric equilibrium. Unlike their model, in which bidders make costly entry decisions before learning their private information, mixing in our FSE auction occurs conditional on realized values.

[20] In PSE, the ME equilibrium revenue is higher than the FE revenue because the former equilibrium avoids high lottery prizes associated with entry by low-value bidders.

A final point concerns asymmetric equilibria. Even the 2P auction admits asymmetric equilibria when dominated bids are allowed (Blume and Heidhues 2004). Experimental evidence, however, suggests that coordination on such asymmetric outcomes is rare without communication under random rematching (Agranov and Yariv 2018). Our matching rule, described in the next section, similarly limits opportunities for sustained coordination on bidder-specific asymmetric roles, motivating our focus on symmetric equilibria.

II. Experimental design

Our between-subjects experiment comprised three treatments corresponding to the three lotteries in (2). In treatment $\tau \in \{\text{FSE, PSE, 2P}\}$, each matched pair played the auction game with lottery l_τ.[21] In each round, after observing their own values, subjects indicated whether to enter the auction and, if so, selected a bid from the value space V. Although opting out is represented by a zero bid in the model, the experiment elicited the entry decision explicitly rather than through the submission of a zero bid. We implemented the experiment using oTree (Chen, Schonger and Wickens 2016).

Each session comprised 20 auction rounds. At the beginning of each session, subjects were randomly divided into groups of six, and three pairs were randomly formed within each group in every round. This matching rule was designed to balance statistical power against the possibility of repeated-game effects. Throughout the analysis, the six-subject matching group serves as the independent unit of observation. There were 27 independent groups in FSE, 14 in PSE, and 14 in 2P.

Because the FSE and PSE auctions are strategically more complex than 2P, we took several steps to facilitate subjects' understanding of the experimental rules. Subjects received printed instructions and watched a video of the instructions. They also completed two practice rounds and a quiz on the experimental rules.[22] In the practice rounds, subjects faced predetermined opponent bids. A matching group proceeded to the 20

[21] OSM A provides an English translation of the instructions for FSE. To minimize potential framing effects, the lottery payoff $l_\tau(b_j)$ for bidder i was described as a profit adjustment. Screenshots of the experimental interface are provided in Figures B2–B4 in OSM B.2.

[22] OSM B.1 presents the quiz questions for FSE.

main auction rounds only after every member had answered all quiz questions correctly.

We also provided subjects with detailed information about the value distribution. The joint distribution on V^2 induced by the mixture distribution described in Section I.A was presented in tabular form.[23] The conditional distribution of the opponent's value v_j, given the bidder's own value v_i, was also displayed on the decision screen. We provided this information to tightly control subjects' beliefs about opponents' values. In FSE and PSE, the decision screen also included a calculator that returned the lottery payoff associated with any hypothetical bid.

To help subjects recognize the dominance of value bidding conditional on entry, we used the *ascending-clock presentation* (Breitmoser and Schweighofer-Kodritsch 2022) in all treatments.[24] Subjects first submitted sealed bids and then watched an ascending-price clock resolve the auction, with their submitted bids serving as automatic exit prices. Thus, the design combined a static sealed-bid format with a dynamic presentation of how the submitted bids determine the auction price.[25] In addition to the opponent's bid and the auction price, subjects received feedback on the winner and their own profit from winning (i.e., profit before the lottery payoff), lottery payoff, and total profit.

To mitigate the influence of social preferences on decisions, we also adopted the amended random-payment scheme (Lim and Xiong 2021). One of the 20 auction rounds was randomly selected for payment for each subject. Subjects were informed whether the current round was the opponent's payment round, whereas their own payment round was revealed only after all rounds had been completed. Consequently, in rounds in which the opponent was unpaid, a subject's choice could affect their own payment but not the opponent's payment, thereby limiting the influence of social preferences. Unless otherwise stated, our analyses focus on these rounds.

We also collected individual-level information. Before the auction rounds, subjects completed multiple-price-list tasks in both the gain and loss domains to elicit their risk

[23] Figure B1 in OSM B.2 shows the table.

[24] To avoid directing subjects toward a particular bidding strategy, we did not explicitly inform them that value bidding is dominant conditional on entry or advise them to follow it (Masuda et al. 2022).

[25] As noted by the authors, this scheme is analogous to eBay's automatic (or proxy) bidding system. Li (2024) refers to the ascending-clock presentation as the "ascending auction framing."

attitudes (MPL; Laury and Holt 2005). These tasks were separately incentivized and administered before the auction rounds to prevent auction earnings from affecting risk elicitation through wealth effects.[26] After the auction rounds, subjects completed the cognitive reflection test (CRT; Frederick 2005; Toplak, West and Stanovich 2014), earning JPY 60 for each correct answer. We used the CRT to investigate the relationship between cognitive reflection and bidding behavior, as in the auction experiment of Schneider and Porter (2020). Tables B1 and B2 in OSM B.2 present the MPL and CRT tasks, respectively. Finally, subjects completed a post-experimental questionnaire.

The experiment was conducted at the laboratories of Osaka University and Kansai University in 2023. A total of 367 students from the two universities participated. They were recruited through ORSEE (Greiner 2015) from the subject pools maintained by the Institute of Social and Economic Research at Osaka University and the Research Institute for Socionetwork Strategies at Kansai University. Because the matching rule required groups of six, subjects remaining after the formation of human-only groups were assigned to groups that included computerized bidders. Of the 367 subjects, 330 were assigned to human-only groups. In accordance with the preregistered protocol, we exclude data from subjects who accumulated 20 or more incorrect answers across repeated attempts at the comprehension quiz (2 in FSE, 2 in PSE, and 3 in 2P). Our analyses thus focus on the remaining 323 subjects: 160 in FSE, 82 in PSE, and 81 in 2P.[27]

Subjects received an initial endowment of JPY 3,000 (approximately USD 23 at the time), which was sufficient to cover the maximum possible loss. Any losses incurred in the auction or the MPL task were deducted from this endowment. The exchange rate was JPY 1 per 10 points. Their average total payment, including the endowment, was JPY 3,499, with individual payments ranging from JPY 1,930 to JPY 4,720. Each session lasted approximately 80 minutes. Detailed session information is provided in Tables B3 and B4 and Figure B5 in OSM B.2.

[26] The outcomes of the risk elicitation tasks were resolved at the end of the session.

[27] Owing to technical issues, subjects in two FSE sessions, comprising eight matching groups, were unable to view the instructional video. However, they were able to listen to its audio while referring to the printed instructions. We find no meaningful behavioral differences between the affected and unaffected sessions (see Figures C10 and C11 and Table C14 in OSM C.6). We therefore include data from the affected sessions in the analysis.

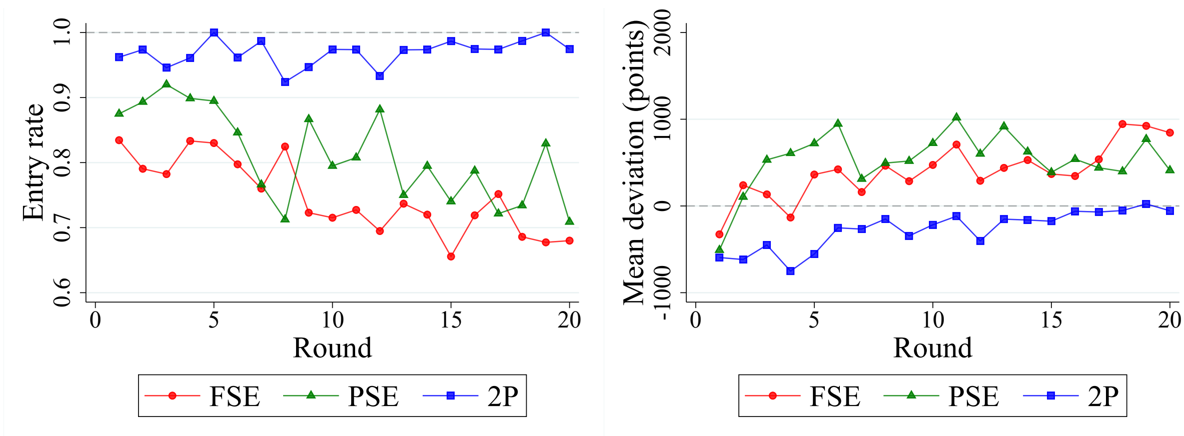
III. Results

This section presents our experimental results. We begin with an overview of behavioral patterns, followed by analyses of entry decisions and bidding behavior. We then evaluate the economic performance of the three auctions.

A. Behavioral overview

We begin with an overview of the extent to which behavior in each treatment conforms to the theoretical benchmarks developed in Section I. Throughout this section, let $v_{it} \in V$ and $b_{it} \in B$ denote subject i's value and bid in round t, respectively. Conditional on entry ($b_{it} > 0$), we define the *(signed) deviation from value bidding* as $b_{it} - v_{it}$ and the *absolute deviation from value bidding* as $|b_{it} - v_{it}|$, following Breitmoser and Schweighofer-Kodritsch (2022). We further classify a positive bid as *value bidding*, *overbidding*, or *underbidding* when $b_{it} = v_{it}$, $b_{it} > v_{it}$, or $b_{it} < v_{it}$, respectively.

Figure 2 plots entry rates and mean deviations among entrants over rounds. In the 2P treatment, the entry rate remains close to 100% throughout, while the mean deviation, which is initially negative, converges to zero over rounds. Together, these patterns suggest that behavior in 2P moves toward the dominant-strategy benchmark of full entry and value bidding.



(a) Entry rate

(b) Mean deviation among entrants

Figure 2: Entry rates and mean deviations from value bidding among entrants.

Notes: The mean deviations in panel (b) are calculated conditional on entry. The dashed lines in panels (a) and (b) indicate one and zero, respectively.

We next turn to the surplus-extracting treatments. As shown in Figure 2a, entry rates decline over rounds in both treatments. In the later rounds, the FSE entry rate hovers around its ME benchmark of 0.74, whereas the PSE entry rate falls well below its corresponding benchmark of 0.95. Because the ME equilibrium yields the lowest ex ante entry probability among all symmetric equilibria under risk neutrality, the entry rate observed in PSE is difficult to reconcile with risk-neutral symmetric equilibrium behavior. Proposition 1, however, shows that opting out is undominated in both treatments. Thus, the low entry rate in PSE remains compatible with the weaker rationality requirement that bidders choose only undominated bids.

At the same time, Figure 2b shows that mean deviations among entrants become positive in both FSE and PSE, indicating overbidding on average. Because any non-value bid is dominated conditional on entry, the positive mean deviations in FSE and PSE do not conform to the benchmark established in Proposition 1.

In the following two subsections, we examine entry decisions and bidding behavior more closely, focusing on factors associated with the observed departures from the theoretical benchmarks.

B. Entry decisions

We first compare entry rates across treatments.[28] Figure 3 plots the empirical cumulative distributions of group-level entry rates for each treatment. A Welch two-sample t-test indicates that mean entry is 6.3 percentage points higher in PSE than in FSE (95% confidence interval: 0.5 to 12.0 percentage points). A Wilcoxon rank-sum test provides somewhat weaker evidence of a difference between the two treatments ($p = 0.072$). Entry is substantially higher in 2P than in either PSE or FSE ($p < 0.001$ for both rank-sum comparisons).

We next compare observed entry rates with the symmetric equilibrium benchmarks. We focus on FSE and PSE because entry in 2P is close to full entry (Figures 2a and 3).

[28] Unless otherwise noted, statistical analyses other than regressions are conducted at the group level, treating matching groups as independent observations. The numbers of independent groups are 27 in FSE and 14 each in PSE and 2P.

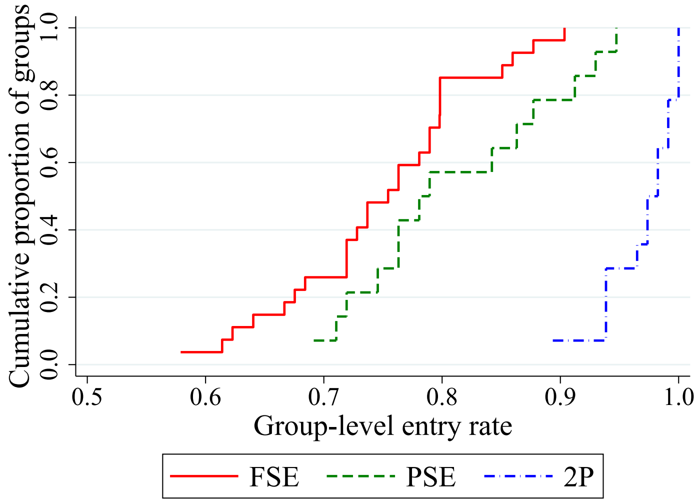
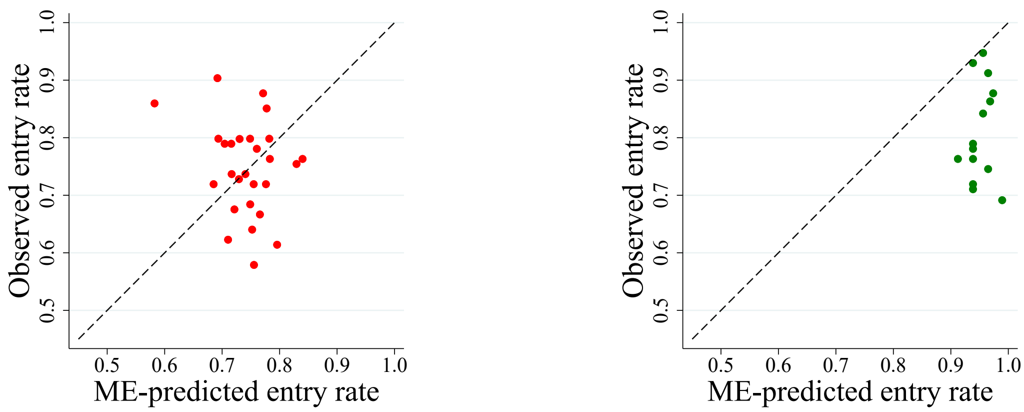


Figure 3: Empirical cumulative distributions of group-level entry rates.

Notes: Entry rates are calculated over all subjects and rounds within each matching group.

In both treatments, the observed rates lie far below the FE-equilibrium benchmark. We therefore use the ME equilibrium, which yields the lowest symmetric equilibrium entry rate under risk neutrality, as a conservative equilibrium benchmark. For each matching group, Figure 4 plots the observed entry rate against its corresponding ME prediction. Wilcoxon signed-rank tests provide no evidence of a difference between the observed and ME-predicted rates in FSE ($p = 0.971$), but strong evidence that the observed rates are lower than the ME predictions in PSE ($p < 0.001$).



(a) FSE

(b) PSE

Figure 4: Observed versus ME-predicted entry rates.

Notes: Each dot represents an independent matching group. For each group, the ME prediction is computed by averaging the equilibrium entry probabilities over the values realized in that group. The dashed line is the 45-degree line.

As Figure 2a shows, entry rates in both FSE and PSE decline over rounds, suggesting that behavior in the early rounds may reflect adjustment rather than equilibrium play. We therefore repeat the comparison with the ME equilibrium using only rounds 11–20, by which time subjects had accumulated substantial experience. In FSE, observed group-level entry rates in these rounds fall below the corresponding ME predictions ($p = 0.041$, Wilcoxon signed-rank test). In PSE, the conclusion from the full-sample analysis is unchanged: observed entry rates remain below the ME predictions ($p < 0.001$, Wilcoxon signed-rank test).

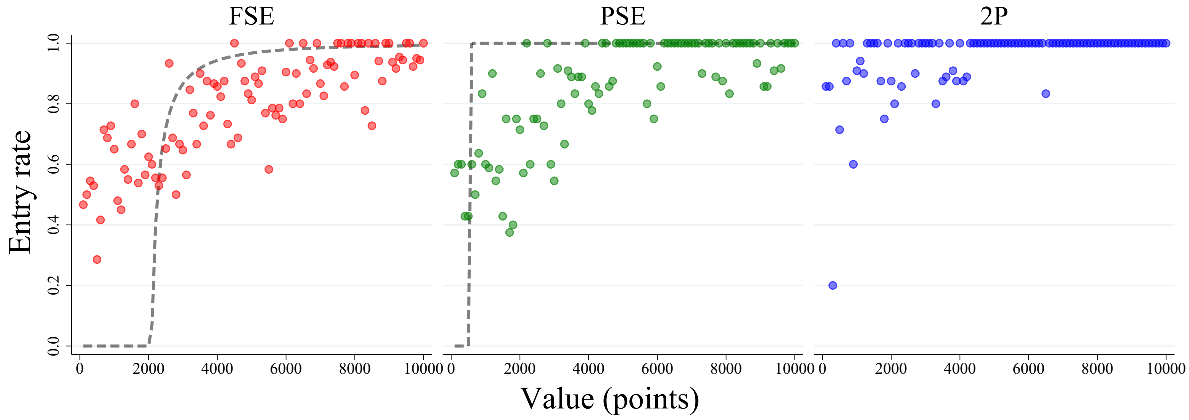
Result 1. *Entry rates are lowest in FSE and highest in 2P, with PSE in between. The group-level rates in PSE are below the ME equilibrium benchmarks. The same holds for FSE when the analysis is restricted to rounds 11–20.*

To compare behavior more closely with equilibrium entry strategies, we now examine how entry varies with value. Figure 5 plots entry rates by value separately for rounds 1–10 and 11–20. In both halves, entry rates in FSE and PSE generally increase with value, as do the ME equilibrium strategies shown by the dashed lines. Thus, the low aggregate entry rates in these treatments do not reflect uniformly low entry across values. From the first half to the second, however, entry rates shift downward across much of the value range in FSE and PSE, whereas entry in 2P moves closer to full entry across values.

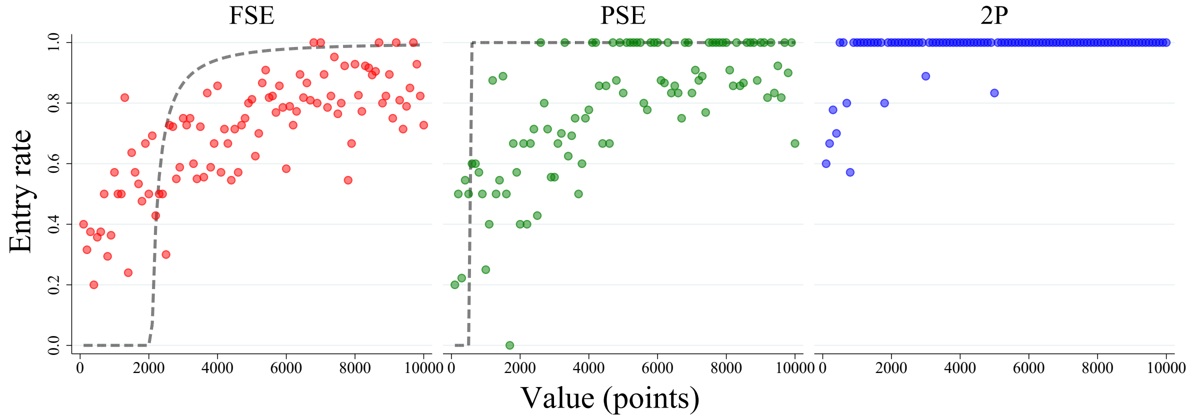
As the preceding analyses make clear, subjects' entry behavior evolves over rounds. In particular, entry rates decline markedly in FSE and PSE. To characterize these dynamics and explore factors associated with them, Table 2 reports mixed-effects linear probability models separately for rounds 1–10 and 11–20.

Column (1) confirms the downward trends in FSE and PSE during rounds 1–10. Entry probability declines by approximately 0.8 and 1.2 percentage points per round in FSE and PSE, respectively ($p = 0.004$ for FSE; $p = 0.006$ for PSE).[29] As Column (3) shows, however, these downward trends are much less pronounced in rounds 11–20 and are no longer statistically significant at the 5% level ($p = 0.230$ for FSE; $p = 0.092$ for PSE).

[29] When a reported treatment-specific effect involves interaction terms, its p-value is based on a Wald test of the corresponding linear combination of coefficients.



(a) Rounds 1–10



(b) Rounds 11–20

Figure 5: Entry rates by value.

Notes: In the FSE and PSE panels, the dashed lines show the ME entry strategies.

The estimated relationship between value and entry is also consistent with Figure 5: in both halves, entry probability increases with value in FSE and PSE.

Another possible factor contributing to low entry in the surplus-extracting treatments is learning from experience. At the outset, subjects had little information about how anonymous others would bid and little experience with the resulting outcomes. As subjects gained experience, exposure to higher opponent bids may have made entry less attractive, either by lowering expected lottery payoffs or through reinforcement from unfavorable realized lottery payoffs. By contrast, in the simple 2P auction with no lottery, the opponent's behavior is theoretically irrelevant for the entry decision.

To examine whether current entry is associated with recent opponent behavior in a manner consistent with this possibility, columns (2) and (4) add the opponent's bid in

Table 2: Mixed-effects linear probability models for entry decisions.

Dependent variable	Entry			
	First 10 rounds		Last 10 rounds	
	(1)	(2)	(3)	(4)
(Constant)	0.590^{***}	0.612^{***}	0.451^{***}	0.466^{***}
	(0.037)	(0.041)	(0.045)	(0.046)
PSE	0.101	0.063	0.203^{*}	0.203^{*}
	(0.059)	(0.068)	(0.090)	(0.097)
2P	0.302^{***}	0.283^{***}	0.414^{***}	0.370^{***}
	(0.047)	(0.053)	(0.067)	(0.079)
Round	-0.008^{**}	-0.008^{*}	-0.003	-0.003
	(0.003)	(0.003)	(0.002)	(0.002)
PSE × Round	-0.004	-0.006	-0.004	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
2P × Round	0.008^{*}	0.007	0.006	0.006
	(0.003)	(0.004)	(0.003)	(0.003)
Value / 1000	0.049^{***}	0.050^{***}	0.059^{***}	0.059^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
PSE × Value / 1000	-0.004	-0.007	-0.011	-0.011
	(0.007)	(0.007)	(0.009)	(0.009)
2P × Value / 1000	-0.034^{***}	-0.036^{***}	-0.047^{***}	-0.046^{***}
	(0.005)	(0.006)	(0.005)	(0.005)
Previous opponent's bid / 1000		-0.007		-0.013^{***}
		(0.004)		(0.003)
PSE × Previous opponent's bid / 1000		-0.002		0.000
		(0.005)		(0.006)
2P × Previous opponent's bid / 1000		0.006		0.015^{***}
		(0.004)		(0.003)
Previous opponent entered		0.008		0.066^{*}
		(0.027)		(0.031)
PSE × Previous opponent entered		0.103		-0.004
		(0.054)		(0.049)
2P × Previous opponent entered		-0.002		-0.047
		(0.043)		(0.047)
Observations	3,050	2,740	3,082	3,082

Notes: The dependent variable is $\mathbf{1}\{b_{it} > 0\}$, where $\mathbf{1}\{\cdot\}$ is the indicator function. FSE is the reference treatment. For subject i, we define *previous opponent's bid* and *previous opponent entered* as $b_{j,t-1}$ and $\mathbf{1}\{b_{j,t-1} > 0\}$, respectively, where j is i's opponent in round $t-1$. All specifications include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

the previous round, an indicator for whether that opponent entered, and interactions of both variables with treatment.[30] Although the lottery payoff is more directly relevant to a subject's entry incentive than the opponent's raw bid in FSE and PSE, 2P has no lottery component. We therefore use the previous opponent's bid as a common measure to compare the association between recent opponent bidding and current entry across treatments. We focus on the immediately preceding round because, as behavior evolves over time, subjects may place greater weight on recent experience when learning about the strategic environment or responding to realized outcomes.[31] The entry indicator is included mainly as a control.

As shown in columns (2) and (4), the estimated associations between the previous opponent's bid and current entry are negative in both FSE and PSE. In the first half, a 1,000-point increase in the previous opponent's bid is associated with a 1.0 percentage-point decrease in entry probability in PSE ($p = 0.001$). In the second half, the associations are significantly negative in both FSE and PSE ($p < 0.001$ for FSE; $p = 0.023$ for PSE).

The evidence on the previous opponent's entry is less robust. When the previous opponent switches from opting out to submitting the minimum positive bid, the lottery payoff jumps from zero to a positive amount in FSE and PSE. The association with the opponent's entry is therefore expected to be positive. The estimated associations are generally positive, as predicted, but the statistical evidence is mixed.

Finally, in 2P, we find no evidence of the negative association between the previous opponent's positive bid and current entry observed in FSE and PSE. The estimated associations with the previous opponent's positive bid are close to zero and, if anything, positive in 2P ($p = 0.603$ for rounds 1–10; $p = 0.092$ for rounds 11–20). We also find no evidence that current entry is associated with whether the previous opponent entered ($p = 0.865$ for rounds 1–10; $p = 0.599$ for rounds 11–20). This pattern is consistent with

[30] Because bidders' values are correlated within an auction, the information conveyed by the previous opponent's bid may depend on the subject's own value in that round. Table C10 in OSM C.6 reports a specification that additionally controls for the subject's value in the previous round and its interactions with treatment. These additional controls leave the estimated relationships between the previous opponent's behavior and current entry virtually unchanged.

[31] As a robustness check, OSM C.1 instead uses mean opponent bids and opponent entry rates over the previous two or three rounds. The main results remain qualitatively unchanged.

the theoretical prediction that, in 2P, entry should not depend on opponent behavior.

Result 2. *Entry declines over rounds in FSE and PSE, with the downward trend more pronounced in the first half. Higher positive bids by the previous-round opponent are generally associated with lower current entry in FSE and PSE. No corresponding negative association is observed in 2P.*

To explore additional correlates of entry decisions, Table 3 reports average marginal effects from mixed-effects probit models pooling all 20 rounds. The negative associations between the previous opponent's positive bid and current entry in FSE and PSE remain evident in the pooled estimates. The previous opponent's entry indicator is also positively associated with current entry in both treatments, as predicted ($p = 0.008$ for FSE; $p = 0.001$ for PSE). Table C11 in OSM C.6 provides an alternative specification that omits these two measures of previous opponent behavior and instead includes the previous-round lottery payoff and profit from winning. Consistent with the results above, a higher lottery payoff in the previous round is associated with higher current entry in both FSE and PSE, whereas profit from winning in the previous round shows no statistically significant association with current entry at conventional levels.

Unlike the main analysis, Table 3 also includes observations from opponents' payment rounds, allowing us to examine whether entry behavior differs when the current round is payoff relevant for the opponent. Entry is higher in such rounds in PSE ($p = 0.019$), but lower in 2P ($p = 0.025$); the corresponding effect in FSE is positive but not statistically significant at the 5% level. The lower entry rate in 2P is consistent with prosocial behavior toward the opponent, as opting out eliminates competition and thereby benefits the opponent. In PSE, however, a subject's bid can generate either a positive or negative lottery payoff for the opponent, so the net effect of entry on the opponent's profit is ambiguous. We discuss related evidence on social preferences in the next subsection.

Risk attitudes can also affect entry in the surplus-extracting treatments because entry exposes subjects to uncertainty in lottery payoffs, including the possibility of losses. Indeed, risk-averse subjects in FSE are 7.7 percentage points less likely to enter than those not classified as risk averse ($p = 0.036$). The corresponding estimate in PSE, however, is

Table 3: Mixed-effects probit regression models for entry decisions.

Dependent variable	Entry		
	FSE	PSE	2P
Round	-0.008^{***}	-0.008^{***}	0.000
	(0.001)	(0.001)	(0.001)
Value / 1000	0.051^{***}	0.043^{***}	0.016^{***}
	(0.003)	(0.005)	(0.004)
Previous opponent's bid / 1000	-0.011^{***}	-0.012^{***}	0.000
	(0.002)	(0.002)	(0.001)
Previous opponent entered	0.060^{**}	0.093^{**}	-0.004
	(0.022)	(0.027)	(0.022)
Opponent's payment round	0.069	0.091^{*}	-0.043^{*}
	(0.036)	(0.039)	(0.019)
CRT score	-0.008	-0.017	0.002
	(0.010)	(0.013)	(0.003)
Risk averse	-0.077^{*}	0.045	-0.019
	(0.036)	(0.038)	(0.011)
Observations	3,040	1,558	1,539

Notes: The dependent variable is $\mathbf{1}\{b_{it} > 0\}$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Observations from opponents' payment rounds are included. *Opponent's payment round* is one if t is a payment round for the current opponent and zero otherwise. *Risk averse* is one if i is risk averse in both the gain and loss domains in MPL and zero otherwise. The table reports average marginal effects estimated from mixed-effects probit models. All specifications include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

not statistically significant at conventional levels ($p = 0.233$).

As shown above, entry in FSE is around or below the risk-neutral ME benchmark, while entry in PSE falls substantially below it. This pattern contrasts with evidence of over-entry in previous auction-entry experiments. For example, Aycinena and Rentschler (2018) study endogenous entry into first-price and English clock auctions and find over-entry relative to risk-neutral equilibrium predictions in all four treatments. Conditional on entry, subjects in their first-price auctions also bid above the risk-neutral equilibrium benchmark. The authors suggest that bidders' heterogeneous risk attitudes may help explain these patterns.

While the ME equilibrium is derived under risk neutrality, OSM C.2 numerically examines how symmetric equilibrium behavior changes as the degree of risk aversion varies, starting from the risk-neutral ME equilibrium. For degrees of risk aversion comparable to those elicited by the MPL tasks, the resulting symmetric equilibria do not account well for the observed pattern of low entry in PSE. Matching the observed entry rate requires substantially greater risk aversion and generates an entry pattern that differs markedly from that in Figure 5. We also note that Lemma A3 continues to hold under risk aversion, so risk aversion can affect equilibrium entry but not the prediction of value bidding conditional on entry. As discussed above, however, low entry in the surplus-extracting treatments may also reflect learning from opponents' bidding behavior rather than risk attitudes alone.

C. Bidding behavior

As the preceding subsection suggests, we need to examine bidding behavior more closely to better understand entry decisions. The theoretical prescription is clear: an entrant should bid their value. However, Figure 2b indicates that mean deviations conditional on entry shift from underbidding toward overbidding over rounds in the surplus-extracting treatments. Since entry itself changes over rounds, these conditional patterns may partly reflect changes in the composition of entrants. For example, the remaining pool of entrants in FSE and PSE may become increasingly composed of subjects who tend to bid more aggressively. We therefore interpret results conditional on entry with this potential selection effect in mind.

We first formally assess whether mean deviations from value bidding among entrants differ across treatments over all 20 rounds. Figure 6 plots the empirical cumulative distributions of group-level mean deviations for each treatment. The distributions suggest that deviations tend to be lower in 2P than in FSE and PSE, while the distributions for FSE and PSE appear broadly similar and are tilted toward overbidding.

Wilcoxon rank-sum tests provide evidence of differences between 2P and each of the other two treatments at the 1% level ($p = 0.008$ for 2P vs. FSE; $p = 0.002$ for 2P vs. PSE), but no evidence of a difference between FSE and PSE at conventional levels ($p = 0.596$). Wilcoxon signed-rank tests indicate that mean deviations are significantly

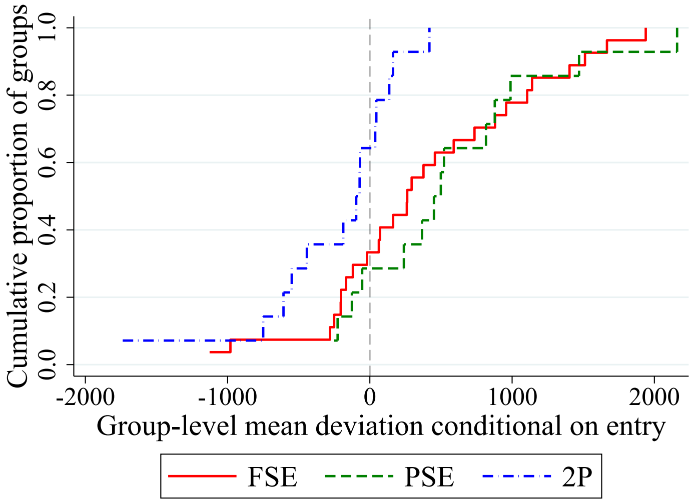


Figure 6: Empirical cumulative distributions of group-level mean deviations among entrants.

Notes: Mean deviations from value bidding are calculated over all subjects and entry rounds within each matching group. The vertical dashed line indicates zero deviation.

positive in FSE and PSE ($p = 0.015$ and $p = 0.006$, respectively), whereas they tend to be negative in 2P but are not statistically different from zero at the 5% level ($p = 0.090$).

Result 3. *Mean deviations from value bidding among entrants are larger in FSE and PSE than in 2P, with no statistically discernible difference between FSE and PSE. In both FSE and PSE, mean deviations among entrants tend to be positive, indicating overbidding.*

We next compare these bidding patterns with findings from the experimental literature on simple second-price auctions. Since our experiment adopts the ascending-clock presentation developed by Breitmoser and Schweighofer-Kodritsch (2022), their results provide a natural benchmark.[32] Figure 7 plots bidding shares among all choices, including opting out, in each round. These unconditional shares complement the conditional analysis above by avoiding conditioning on entry.

In our 2P treatment, underbidding accounts for the largest share in round 1, while value bidding is also substantial and overbidding accounts for the smallest share. As rounds progress, the share of underbidding declines, and value bidding becomes more prevalent. A similar shift from underbidding toward value bidding is observed in the

[32]They use standard auctions in rounds 1–10 and modified "X-auctions" in rounds 11–20, following Li (2017).

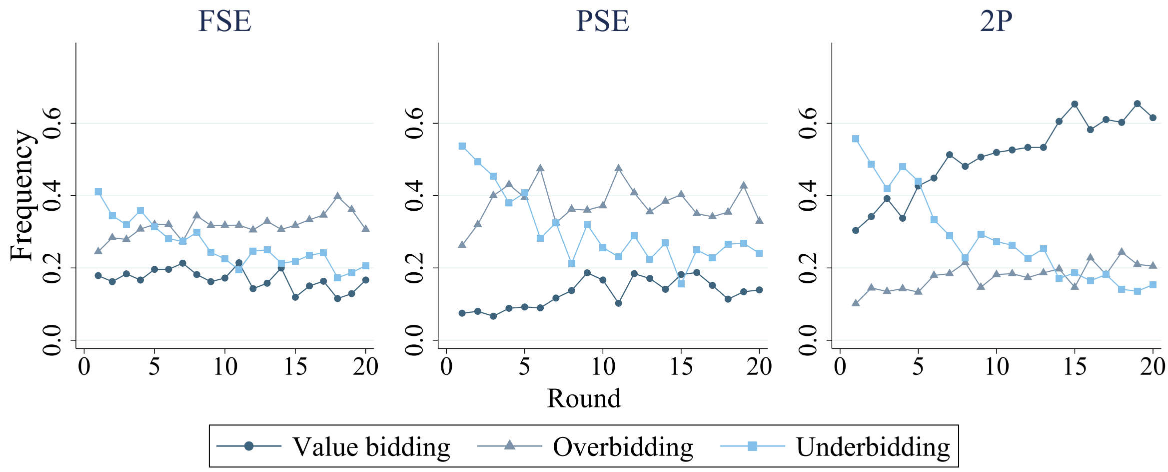


Figure 7: Unconditional bidding shares over rounds.

Notes: The lines show the shares of value bidding, overbidding, and underbidding among all choices, including opting out, in each round. The share of opting out is not plotted.

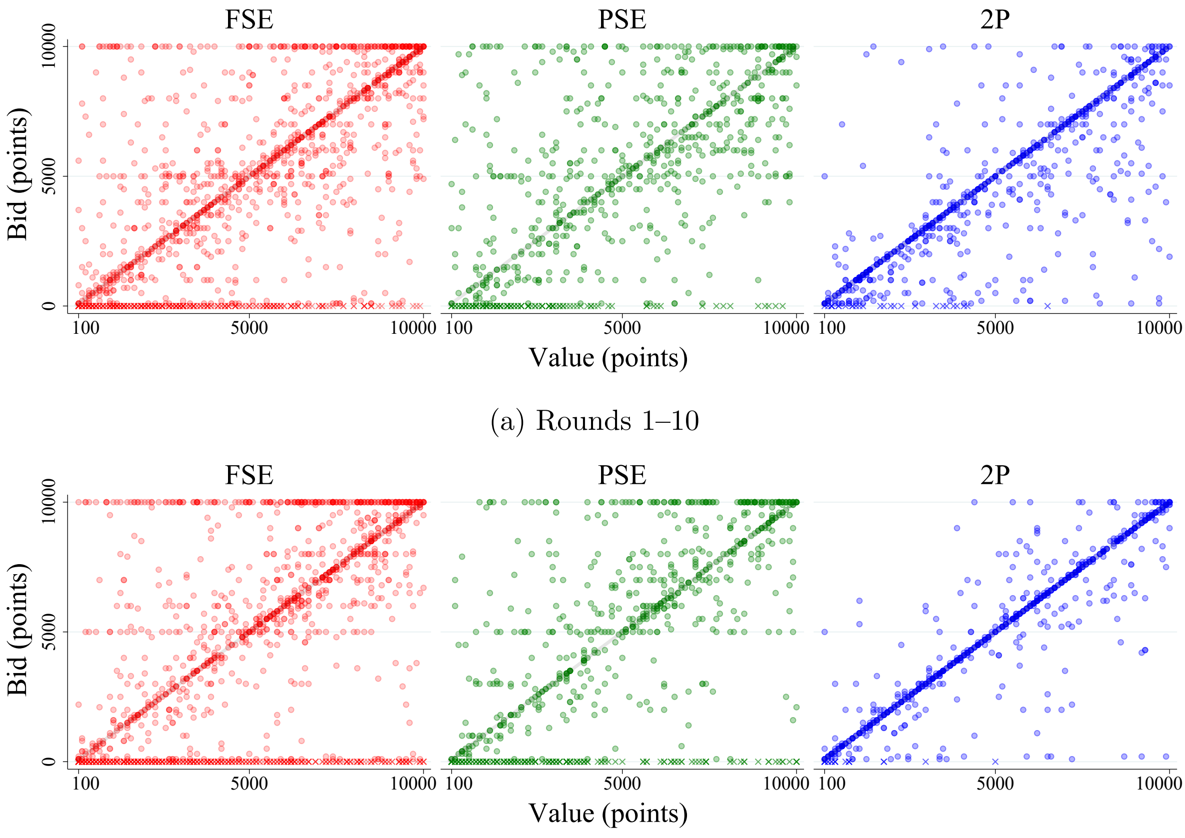
2PAC and 2PAC-B treatments of Breitmoser and Schweighofer-Kodritsch (2022), in which sealed bids are subsequently resolved through a passive ascending clock. By contrast, they find systematic overbidding only in their conventional second-price treatment, which does not use the ascending-clock presentation.

As Breitmoser and Schweighofer-Kodritsch (2022, p. 497) note, initial underbidding has been documented in numerous experiments on second-price auctions.[33] In our 2P treatment, underbidding, overbidding, and value bidding account for 56%, 10%, and 30% of all choices in round 1, respectively. The corresponding shares are 41%, 25%, and 18% in FSE and 54%, 26%, and 8% in PSE. Wilcoxon rank-sum tests indicate that group-level overbidding shares in round 1 are higher in FSE and PSE than in 2P ($p = 0.011$ for FSE vs. 2P; $p = 0.012$ for PSE vs. 2P), while providing no evidence of a difference between FSE and PSE ($p = 0.764$). Thus, although underbidding is the most common behavior in both FSE and PSE in round 1, overbidding is more prevalent than in 2P. Since this difference is already present in round 1, the pattern suggests that the auction rules themselves contribute to the higher prevalence of overbidding in the surplus-extracting treatments, rather than this difference emerging solely through experience.

[33] See Breitmoser and Schweighofer-Kodritsch (2022, footnote 15) for related references. They suggest that the relatively pronounced initial underbidding in their experiment may reflect the absence of pre-play training; our experiment included both practice rounds and comprehension quizzes.

As shown in Figure 7, the share of underbidding declines over rounds in FSE and PSE. At the same time, the share of overbidding gradually increases, and overbidding is more frequent than underbidding in rounds 11–20. In round 20, value bidding accounts for only 17% of all choices in FSE and 14% in PSE, compared with 62% in 2P. In 2P, this share is nearly twice its round 1 level of 30%.

Figure 8 plots bids against values. In rounds 11–20, bids are concentrated around the value-bidding line in 2P. In FSE and PSE, by contrast, we observe both value bidding and frequent opting out in these rounds. There is also a noticeable concentration of observations at the maximum bid in both treatments.[34]



(a) Rounds 1–10

(b) Rounds 11–20

Figure 8: Bids versus values.

Notes: Circles and crosses denote positive and zero bids, respectively. The 45-degree line represents value bidding.

We next use regression models to investigate factors associated with deviations from

[34]Using data from rounds 11–20, OSM C.4 applies the k-means clustering algorithm (MacQueen 1967) to explore how subjects' behavior can be classified. The analysis identifies a cluster characterized by substantial overbidding, accounting for approximately 13% of subjects in FSE and 20% in PSE.

value bidding among entrants, focusing on the pronounced overbidding in FSE and PSE. As in Table 2, we analyze the first and second halves of the experiment separately. Table 4 reports mixed-effects linear models for deviations from value bidding among entrants. As shown in Figure 8, deviations may vary with value, so we include interactions between value and treatment as controls.

Our main focus is on whether recent opponent behavior is associated with current deviations from value bidding among entrants. As in the entry analysis, columns (2) and (4) therefore include the previous opponent's bid and an indicator for whether the previous opponent entered.[35] Unlike the entry decision, however, optimal bidding for an entrant should not depend on previous opponent behavior, because value bidding is dominant conditional on entry.

For the first half, column (1) shows that deviations increase over rounds in both FSE and PSE ($p = 0.014$ for FSE; $p = 0.028$ for PSE), but column (2) shows that these trends become less pronounced once previous opponent behavior is included. Higher positive bids by the previous opponent are associated with larger deviations in both treatments. A 1,000-point increase in the previous opponent's bid is associated with an increase in the current deviation of 104 points in FSE and 84 points in PSE ($p < 0.001$ for FSE; $p = 0.005$ for PSE). By contrast, no corresponding association is observed in 2P ($p = 0.622$).

The pattern changes in the second half. As column (3) shows, the positive round trend is no longer statistically significant in FSE ($p = 0.106$) and becomes negative in PSE ($p = 0.028$). The estimated associations between the previous opponent's positive bid and current deviations are substantially smaller and no longer statistically significant in either FSE or PSE ($p = 0.280$ for FSE; $p = 0.350$ for PSE). The attenuation is particularly evident in PSE: when recent opponent bids are measured by mean bids over the previous two or three rounds, the positive association remains in FSE but not in PSE (OSM C.3).

In contrast to FSE and PSE, the simple 2P treatment provides no evidence of a corre-

[35] As a robustness check, Table C12 in OSM C.6 repeats the analysis for subjects who entered in all rounds, thereby holding the composition of entrants fixed at the subject level. OSM C.3 instead uses mean opponent bids and opponent entry rates over the previous two or three rounds for the full sample.

Table 4: Mixed-effects linear models for deviations from value bidding among entrants.

Dependent variable	Deviation			
	First 10 rounds		Last 10 rounds	
	(1)	(2)	(3)	(4)
(Constant)	1633.6^{***}	1602.5^{***}	1648.0^{***}	1539.6^{***}
	(269.2)	(244.3)	(437.1)	(439.6)
PSE	690.0	422.1	1133.8	1168.6
	(477.3)	(561.7)	(794.5)	(803.6)
2P	-1517.1^{***}	-1884.9^{***}	-1970.8^{**}	-2067.2^{**}
	(305.3)	(504.4)	(574.4)	(718.6)
Round	64.7^{*}	36.1	36.8	37.1
	(26.2)	(26.5)	(22.8)	(22.4)
PSE × Round	18.4	7.5	-72.0^{*}	-71.1^{*}
	(46.0)	(50.5)	(34.0)	(33.3)
2P × Round	−24.3	14.6	−9.8	−10.6
	(33.3)	(33.8)	(29.8)	(29.3)
Value / 1000	-324.6^{***}	-319.7^{***}	-289.0^{***}	-289.8^{***}
	(34.1)	(34.9)	(39.3)	(39.7)
PSE × Value / 1000	−91.9	−93.6	8.6	10.3
	(57.0)	(60.9)	(56.0)	(56.6)
2P × Value / 1000	172.9^{***}	178.3^{***}	240.7^{***}	241.8^{***}
	(44.9)	(47.2)	(41.8)	(42.1)
Previous opponent's bid / 1000		104.2^{***}		24.6
		(16.6)		(22.8)
PSE × Previous opponent's bid / 1000		−19.9		9.6
		(34.2)		(43.2)
2P × Previous opponent's bid / 1000		-114.2^{***}		−21.6
		(26.2)		(25.6)
Previous opponent entered		−331.8		59.4
		(204.7)		(161.2)
PSE × Previous opponent entered		500.0		−158.6
		(464.1)		(363.3)
2P × Previous opponent entered		660.7		178.3
		(457.8)		(306.9)
Observations	2,585	2,313	2,436	2,436

Notes: The dependent variable is $b_{it} - v_{it}$. The sample is restricted to observations with $b_{it} > 0$. FSE is the reference treatment. All specifications include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

sponding association between the previous opponent's positive bid and current deviations among entrants. The estimated association is not statistically different from zero in either half ($p = 0.622$ for rounds 1–10; $p = 0.801$ for rounds 11–20).

Result 4. *In the first half, higher positive bids by the previous-round opponent are associated with larger deviations from value bidding among entrants in FSE and PSE. In the second half, these associations become less pronounced, particularly in PSE. No corresponding relationship is observed in 2P.*

Table 5 explores additional correlates of both signed and absolute deviations among entrants, pooling all 20 rounds. The positive associations between the previous opponent's positive bid and current deviation among entrants in FSE and PSE observed in the first half remain evident in the pooled estimates. These associations are also robust to specifications with subject and round fixed effects (Table C13 in OSM C.6).

We next consider cognitive reflection. The evidence so far suggests that, despite the ascending-clock presentation and experience accumulated over rounds, convergence toward value bidding is much weaker in FSE and PSE than in 2P. This raises the question of whether cognitive reflection is associated with closer adherence to value bidding conditional on entry. This question is motivated by Schneider and Porter (2020), who study the roles of choice architecture (strategy-proof versus obviously strategy-proof implementations), experience, and cognitive reflection in dominant-strategy play. Particularly relevant here, their auction results show that high-CRT subjects exhibit fewer and smaller absolute deviations from value bidding than low-CRT subjects.[36]

As shown in columns (4)–(6), however, we find no consistent evidence that cognitive reflection is associated with closer adherence to value bidding among entrants across treatments. In FSE, higher CRT scores are associated with larger absolute deviations ($p = 0.018$), a pattern opposite to that documented by Schneider and Porter (2020). The corresponding associations are negative in PSE and 2P, but only the PSE estimate is statistically significant at the 5% level ($p = 0.046$ for PSE; $p = 0.404$ for 2P).

[36]Schneider and Porter (2020) use the seven-item CRT developed by Toplak, West and Stanovich (2014). Using a different measure of cognitive ability, Giebe et al. (2024) likewise find that subjects with higher cognitive ability are more likely to bid their values in simple second-price auctions.

Table 5: Mixed-effects linear regression models for signed and absolute deviations from value bidding among entrants.

Dependent variable	Deviation			Absolute deviation		
	FSE	PSE	2P	FSE	PSE	2P
	(1)	(2)	(3)	(4)	(5)	(6)
Round	37.8^{**}	7.0	37.9^{***}	11.4	-32.6^{***}	-43.4^{***}
	(13.5)	(17.6)	(8.9)	(10.7)	(8.8)	(9.7)
Value / 1000	-332.6^{***}	-364.9^{***}	-110.3^{***}	-99.9^{**}	-148.7^{**}	67.7^{**}
	(33.7)	(41.3)	(14.3)	(28.8)	(43.2)	(23.2)
Previous opponent's bid / 1000	74.3^{***}	94.1^{***}	-7.9	45.3^{**}	39.0	-2.3
	(15.7)	(25.2)	(9.1)	(15.6)	(27.1)	(15.1)
Previous opponent entered	-220.2	-345.0	308.0	-373.9^{**}	-63.4	-106.9
	(136.6)	(228.5)	(232.0)	(114.4)	(161.9)	(232.8)
Opponent's payment round	-498.3	-745.4	-722.8	1147.3^{***}	743.1^{**}	1095.7^{**}
	(347.7)	(407.4)	(461.0)	(324.7)	(251.3)	(348.3)
CRT score	59.2	-32.9	-135.9^{*}	80.9^{*}	-91.0^{*}	-56.8
	(60.9)	(78.4)	(72.8)	(34.1)	(45.6)	(68.1)
(Constant)	1449.5^{***}	2576.8^{***}	408.0	1670.2^{***}	3206.2^{***}	1260.0^{***}
	(334.7)	(550.5)	(443.4)	(241.2)	(517.3)	(318.8)
Observations	2,267	1,264	1,489	2,267	1,264	1,489

Notes: The dependent variables are $b_{it} - v_{it}$ and $|b_{it} - v_{it}|$. The sample is restricted to observations with $b_{it} > 0$. Observations from opponents' payment rounds are included. All specifications include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Beyond limitations in contingent reasoning (Li 2017), the experimental literature on second-price auctions identifies spite (Morgan, Steiglitz and Reis 2003) as another possible source of overbidding. Motivated by this concern, we employ the amended random-payment scheme (Lim and Xiong 2021) to mitigate the influence of social preferences, including spite.[37] As Table 5 shows, opponents' payment rounds are not associated with statistically discernible changes in signed deviations, whereas absolute deviations increase significantly by approximately 750–1,150 points. This pattern is consistent with offsetting responses: spiteful subjects may raise their bids, while prosocial subjects may lower them. If so, the payment scheme concentrates the influence of social preferences in opponents' payment rounds, reducing their potential influence in other rounds. Further evidence supporting the effectiveness of this scheme in mitigating concerns about social

[37] Lim and Xiong (2021) study jump bidding in English auctions with independent private values and risk-averse bidders and introduce the amended random-payment scheme to mitigate spite-driven overbidding in their experiment.

preferences is provided by Lafky, Lai and Lim (2022) and Chang, Kim and Lim (2025).

Finally, we consider the strategic relationship between overbidding and opting out in the surplus-extracting auctions. Although overbidding is dominated by value bidding, it is still a best response when bidder i expects bidder j to opt out. This is also true in 2P, but an important difference is that opting out itself is *undominated* in FSE and PSE. Thus, in both auctions, overbidding can be a best response for bidder i even when bidder j is expected to make an undominated choice, namely, opting out. In that case, bidder i obtains the item for free. Conversely, opting out can be a *unique* best response for bidder j when bidder i is expected to submit sufficiently high bids, because the resulting lottery payoffs can make entry unprofitable. In fact, as shown in Section III.B, higher bids by recent opponents are associated with lower current entry in FSE and PSE. While Yamashita (2015) assumes that agents choose only undominated strategies, this argument shows that, in our experimental setting, dominated overbidding can nevertheless be a best response to the conjecture that the opponent will make the undominated choice of opting out.

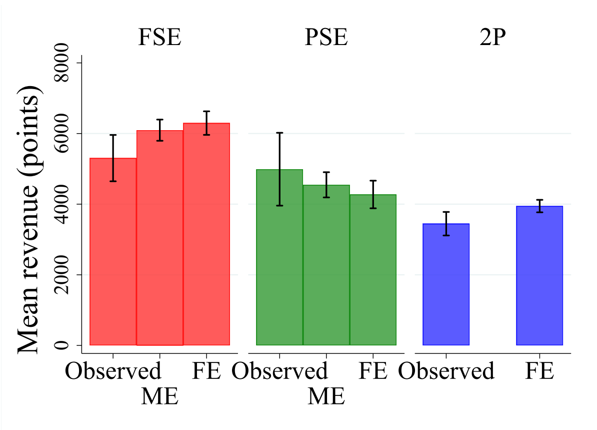
To assess the quantitative relevance of this interaction for entry, OSM C.5 explores how the presence of bidders who systematically overbid affects the entry behavior of "baseline" bidders, using a model based on quantal response equilibrium (McKelvey and Palfrey 1995). In 2P, predicted entry by baseline bidders is essentially unaffected by the presence of systematic overbidders. By contrast, in FSE and PSE, the presence of systematic overbidders substantially lowers predicted entry by baseline bidders relative to a counterfactual without systematic overbidding and brings the predictions closer to the observed entry patterns. This effect is particularly pronounced in PSE. Thus, the model suggests that systematic overbidding by opponents can substantially reduce entry in the surplus-extracting auctions.

D. Seller revenue and bidder profit

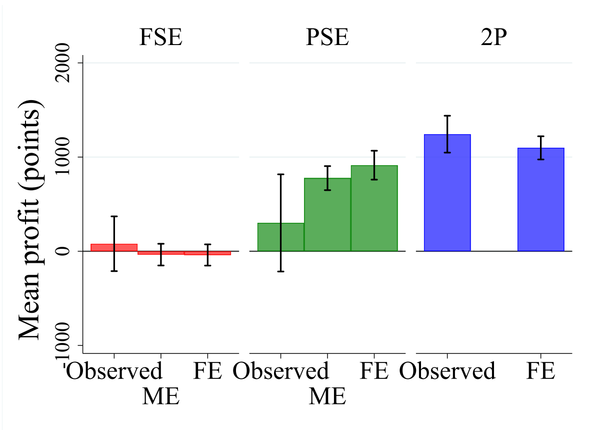
This subsection evaluates the overall economic performance of the three auctions. Because seller revenue and total bidder profit together determine realized total surplus, we consider both outcomes. Although the primary focus of this study is on bidder behavior, this exercise provides a broader empirical assessment of the surplus-extracting auctions.

Figure 9 presents observed mean seller revenue and mean profit per bidder alongside the corresponding equilibrium benchmarks, using all 20 rounds. In FSE, Wilcoxon signed-rank tests indicate that group-level mean revenue is below both equilibrium benchmarks ($p = 0.012$ for FE; $p = 0.034$ for ME). In PSE, by contrast, the tests provide no evidence of a difference between observed mean revenue and either equilibrium benchmark at conventional levels ($p = 0.104$ for FE; $p = 0.391$ for ME). In 2P, the test shows that observed mean revenue falls below the equilibrium benchmark ($p = 0.004$).[38]

For cross-treatment comparisons, Wilcoxon rank-sum tests indicate that observed mean revenue is lower in 2P than in either FSE ($p < 0.001$) or PSE ($p = 0.008$). By contrast, the corresponding test provides no evidence of a difference between FSE and PSE ($p = 0.540$). Mean revenue is 5303 in FSE, 4989 in PSE, and 3446 in 2P. Thus, when performance is evaluated in terms of mean revenue, the surplus-extracting auctions generate substantially higher revenue than the simple 2P auction.



(a) Seller revenue



(b) Profit per bidder

Figure 9: Mean seller revenue and bidder profit.

Notes: Bars show means across independent matching groups. Profit is measured per bidder. For each group, the equilibrium benchmarks for revenue and profit are computed using the values realized in that group. Capped spikes indicate 95% confidence intervals.

Turning to bidder profits, observed mean profit in FSE is close to zero, whereas

[38] While 2P exhibits a shift from underbidding toward value bidding over rounds, observed mean revenue remains significantly below the equilibrium benchmark even in rounds 11–20 ($p = 0.016$). Figure C9 in OSM C.6 presents counterparts to Figure 9 separately for rounds 1–10 and 11–20.

bidders earn positive profits in PSE and 2P. In 2P, there is no statistically significant difference between observed mean profit and the equilibrium benchmark at the 10% level ($p = 0.118$). In PSE, however, observed mean profit is below both equilibrium benchmarks ($p = 0.010$ for FE; $p = 0.049$ for ME, Wilcoxon signed-rank tests). Thus, although PSE is designed to leave bidders more surplus than FSE under full entry, the higher bidder profits predicted by the equilibrium benchmarks are only partially realized in the experiment.

The revenue performance in each treatment is closely linked to the entry and bidding patterns examined in Sections III.A–III.C. The revenue shortfall in 2P is consistent with the systematic underbidding observed in that treatment. By contrast, systematic overbidding among entrants occurs in both FSE and PSE. Although such overbidding may increase seller revenue conditional on entry, it may also reduce revenue indirectly through lower entry, given the negative association between opponents' bids and subsequent entry documented in Sections III.B and III.C.

The mean-revenue advantage of the surplus-extracting auctions over 2P does not contradict the theoretical result established by Yamashita (2015). His approach evaluates mechanisms by their *worst-case* performance over agents' undominated strategies, rather than by mean revenue under observed behavior.[39] Constructing an empirical analogue of this worst-case criterion is not straightforward. One possible measure would be to take, for each value pair realized within a treatment, the minimum observed revenue and then average these minima over the realized value pairs. Such a measure, however, is based on within-treatment sample minima and is sensitive to the number of observations. Constructing it at the treatment level also requires pooling observations across matching groups, making it difficult to preserve the matching group as the independent unit of analysis. Moreover, our experiment documents substantial systematic overbidding among entrants, whereas Yamashita's criterion is defined over undominated strategies. We therefore do not pursue an empirical analogue of the worst-case criterion in this study.

[39]Theoretically, the worst-case expected revenue is equal to the FE equilibrium revenue in the simple 2P auction but negative in the surplus-extracting auctions, because both value bidding and opting out are undominated in the latter. For example, revenue can be negative when bidders with sufficiently low values bid their values.

IV. Conclusion

The full-surplus-extraction result established by Crémer and McLean (1988) has been viewed as raising questions about the practical relevance of the conventional mechanism-design paradigm. This concern has been one of the motivations behind the development of robust mechanism design (Yamashita 2015; Carroll 2019). Despite this longstanding theoretical interest, surprisingly little is known about bidder behavior in full-surplus-extracting auctions. To fill this gap, we provide experimental evidence on entry and bidding behavior in a class of surplus-extracting auctions. The two surplus-extracting auctions differ in the degree of surplus extraction, but in both auctions, value bidding and opting out are undominated strategies. Relative to the simple second-price auction, the coexistence of these two undominated strategies introduces an additional layer of strategic complexity. In both surplus-extracting auctions, we observe lower entry and more overbidding among entrants than in the second-price auction, together with an association between higher opponent bids and lower subsequent entry. These findings highlight the interplay between entry and bidding behavior and point to an important challenge for surplus extraction in auction design with voluntary participation.

Appendix. Lemmas and Propositions

We first introduce some notation. Let w_i and w_j denote random variables drawn independently and uniformly from V. We also write the value space as $V = \{v^1, v^2, \dots, v^n\}$.

The following lemma characterizes the full-surplus-extracting lottery. Suppose that both bidders always submit their values in the simple 2P auction augmented with a lottery $l : V \to \mathbb{R}$. Then, the seller extracts the full surplus if and only if each bidder's interim expected profit is zero for every value $v \in V$:

$$\rho l(v) + (1-\rho)E\left[v - \min\{v, w_j\} + l(w_j)\right] = 0 \tag{A1}$$

Lemma A1. *A function $l : V \to \mathbb{R}$ satisfies equation (A1) for all $v \in V$ if and only if*

$$l(v) = \frac{1-\rho}{\rho}\left((1-\rho)E\left[w_i - \min\{w_i, w_j\}\right] + E\left[\min\{v, w_j\}\right] - v\right), \quad \forall v \in V. \tag{A2}$$

Proof of Lemma A1. Simple algebra shows that the function l defined by equation (A2) satisfies equation (A1) for all $v \in V$. Conversely, suppose that a function l satisfies (A1) for all $v \in V$. Multiplying both sides of (A1) by $1/n$ and summing over v, we obtain

$$\rho \sum_v \frac{l(v)}{n} + (1-\rho)E[l(w_j)] + (1-\rho)\sum_v \frac{1}{n}\left(v - E\left[\min\{v, w_j\}\right]\right) = 0.$$

Since w_i and w_j have the same uniform distribution, this implies $E[l(w_j)] = -(1-\rho)E\left[w_i - \min\{w_i, w_j\}\right]$. Substituting this expression back into (A1) gives (A2). $\square$

Lemma A2. *Value bidding is dominant conditional on entry.*

Proof of Lemma A2. Value bidding is dominant in the simple 2P auction, while the lottery payoff $l_\tau(b_j)$ for bidder i depends only on the opponent's bid b_j. Hence, for a bidder with any value v, the bid $b = v$ dominates every non-value bid $b' \in V$ with $b' \neq v$. $\square$

Proof of Proposition 1. From Lemma A2, it remains only to compare value bidding with opting out. In 2P, value bidding dominates opting out. In FSE and PSE, if the opponent opts out, then value bidding is strictly better than opting out; if the opponent submits the maximum bid, then opting out is strictly better than value bidding because the lottery payoff is then negative and value bidding cannot generate a positive profit from winning. Hence, neither value bidding nor opting out dominates the other in FSE and PSE. □

Lemma A3. *Fix any value $v \in V$. In every symmetric equilibrium, a bidder with value v assigns probability zero to each bid $b \in V$ with $b \neq v$.*

Proof of Lemma A3. To derive a contradiction, suppose that a symmetric equilibrium assigns positive probability to some positive bid $b \in V$ with $b \neq v$ for a bidder with value v. By symmetry, the opponent therefore also submits bid b with positive probability.

When the opponent bids b, the lottery payoff from entry is fixed at $l_\tau(b)$, so the payoff comparison reduces to that in the second-price auction. Deviating from b to v is then strictly profitable: if $b < v$, the deviation turns a tie at b into a win at price b; if $b > v$, it avoids a tie at a price above value. From Lemma A2, for all other opponent bids, the bidder is weakly better off by deviating from b to v. Hence, the bidder with value v is strictly better off through this deviation, contradicting equilibrium. □

We now identify the ME equilibrium for FSE and PSE. For ease of analysis, we use the *opt-out strategy* $z(v) = 1 - y(v)$, where y is an entry strategy. Using Lemma A3, we identify each (symmetric) equilibrium with its associated opt-out strategy.

For each auction $\tau \in \{\text{FSE}, \text{PSE}\}$, we denote by $l_\tau = l + \delta_\tau$ the associated lottery, where l denotes the full-surplus-extracting lottery defined by equation (A2), and $\delta_\tau > 0$ is a treatment-specific constant shift. Since l is decreasing on V, so is l_τ. For later use, let $U^z(v)$ denote a bidder's interim expected profit from entry with value bidding when the opponent follows the opt-out strategy z:

$$U^z(v) = E_{v_j}\left[vz(v_j) + (v - \min\{v, v_j\} + l_\tau(v_j))\,(1 - z(v_j)) \mid v_i = v\right].$$

We will frequently use the following expression, which follows from the condition (A1):

$$U^z(v) = \rho\,(v - l_\tau(v))\,z(v) + (1-\rho)\sum_{w \in V}\frac{1}{n}\,(\min\{v, w\} - l_\tau(w))\,z(w) + \delta_\tau. \tag{A3}$$

Lemma A4. *Fix any equilibrium z. (i) z is nonincreasing on $\{v \in V \mid v \geq l_\tau(v)\}$. (ii) $z(v^n) < 1$. (iii) If $z(v^m) = 0$ for some $v^m \geq l_\tau(v^m)$, then $z(v) = 0$ and $U^z(v) = U^z(v^m) \geq 0$ for each $v > l_\tau(v)$.*

Proof of Lemma A4. (i) To derive a contradiction, suppose that $z(v') > z(v)$ for some $v' > v \geq l_\tau(v)$. Since l_τ is decreasing on V, $v' - l_\tau(v') > v - l_\tau(v) \geq 0$. Equation (A3) then implies $U^z(v') > U^z(v) \geq 0$, where the second inequality follows from $z(v) < 1$. Thus, a bidder with value v' prefers value bidding to opting out, contradicting $z(v') > 0$.

(ii) To derive a contradiction, suppose that $z(v^n) = 1$. Part (i) implies that $z(v) = 1$ for every $v \geq l_\tau(v)$. Since $z(v^n) = 1$, $U^z(v^n) \leq 0$ in equilibrium. Moreover, equation (A3) implies $U^z(v) < U^z(v^n) \leq 0$ for every $v \leq l_\tau(v)$, and hence $z(v) = 1$ for these values as well. Thus, both bidders always opt out. A bidder can then profitably deviate by making a positive bid and obtaining the item for free, contradicting equilibrium.

(iii) Suppose that $z(v^m) = 0$ for some $v^m \geq l_\tau(v^m)$. Since z is an equilibrium, $U^z(v^m) \geq 0$. Part (i) implies that $z(v) = 0$ for every $v \geq v^m$. If $(v^{m-1} - l_\tau(v^{m-1}))z(v^{m-1}) > 0$, then equation (A3) implies $U^z(v^{m-1}) > U^z(v^m) \geq 0$, contradicting $z(v^{m-1}) > 0$. Hence, $z(v^{m-1}) = 0$ whenever $v^{m-1} > l_\tau(v^{m-1})$. Proceeding inductively yields $z(v) = 0$ for every $v > l_\tau(v)$. Equation (A3) then implies $U^z(v) = U^z(v^m) \geq 0$ for every $v > l_\tau(v)$. □

Lemma A5. *Let z be an equilibrium in FSE that satisfies $z(v) > 0$ for some $v > l_{\mathrm{FSE}}(v)$. Then, the equilibrium z has a threshold $v^k > l_{\mathrm{FSE}}(v^k)$ such that $z(v) = 1$ for every $v < v^k$, and $z(v) \in (0, 1)$ for every $v \geq v^k$.*

Proof of Lemma A5. Lemma A4(ii) and (iii) imply $z(v^n) < 1$ and $z(v^n) > 0$, respectively. Hence, $U^z(v^n) = 0$ in equilibrium. Equation (A3) implies that $U^z(v) < U^z(v^n) = 0$ and hence $z(v) = 1$ in equilibrium for every $v \leq l_{\mathrm{FSE}}(v)$. Together with these facts, Lemma A4(i) implies that there exists a threshold $v^k > l_{\mathrm{FSE}}(v^k)$ in the statement. □

Lemma A6. *FSE has a unique equilibrium among those satisfying $z(v) > 0$ for some $v > l_{\mathrm{FSE}}(v)$.*

Proof of Lemma A6. Let z be such an equilibrium. Lemma A5 implies that, for some threshold $v^k > l_{\mathrm{FSE}}(v^k)$, z is a solution to the following system of n linear equations:

$$
\begin{aligned}
&z(v') = 1, \\
&\rho\,(v - l_{\mathrm{FSE}}(v))\,z(v) + (1-\rho)\sum_{w\in V}\frac{1}{n}\,(\min\{v,w\} - l_{\mathrm{FSE}}(w))\,z(w) = -\delta_{\mathrm{FSE}}
\end{aligned}
$$

for every $v' < v^k$ and $v \geq v^k$, respectively.

We now establish existence and uniqueness. Lemma D1 of OSM D shows that, for every integer k with $v^k > l_{\mathrm{FSE}}(v^k)$, the above system has a unique solution $z^k \in \mathbb{R}^n$. Lemma D4 of OSM D ensures that the set of such integers k satisfying the necessary equilibrium condition $U^{z^k}(v^{k-1}) \leq 0$ is nonempty. Since V is finite, this set has a highest element m. Lemma D6 of OSM D shows that the solution z^m corresponding to this highest element m is an equilibrium and that no other threshold yields an equilibrium. Hence, the equilibrium is unique. $\square$

Lemma A7. *The equilibrium z in Lemma A6 is a unique ME equilibrium in FSE. The ME opt-out strategy is nonincreasing on V.*

Proof of Lemma A7. Fix any other equilibrium z'. First, suppose that $z'(v) > 0$ for some $v > l_{\mathrm{FSE}}(v)$. Then, $z' \equiv z$ by the uniqueness established in Lemma A6. Second, suppose that $z'(v) = 0$ for every $v > l_{\mathrm{FSE}}(v)$. Then, $z'(v) = 0 \leq z(v)$ for every $v > l_{\mathrm{FSE}}(v)$. Since Lemma A5 implies that $z(v) = 1$ for every $v \leq l_{\mathrm{FSE}}(v)$, we also have $z'(v) \leq 1 = z(v)$ for these values. Hence, $z'(v) \leq z(v)$ for every $v \in V$. Thus, z is the unique ME equilibrium.

Lemma A4(i), together with Lemma A5, implies that z is nonincreasing on V. $\square$

Lemma A8. *In PSE, every equilibrium z satisfies $z(v) = 0$ for each $v \geq l_{\mathrm{PSE}}(v)$.*

Proof of Lemma A8. Fix any equilibrium z. To derive a contradiction, suppose that $z(v) > 0$ for some $v \geq l_{\mathrm{PSE}}(v)$. The equilibrium condition then implies $U^z(v) \leq 0$.

If $w \geq l_{\mathrm{PSE}}(w)$, then $\min\{v,w\} - l_{\mathrm{PSE}}(w) \geq 0$. If $w < l_{\mathrm{PSE}}(w)$, then $w < v$ and hence $\min\{v,w\} - l_{\mathrm{PSE}}(w) = w - l_{\mathrm{PSE}}(w) < 0$. Therefore, equation (A3) implies

$$
U^z(v) \geq \rho\,(v - l_{\mathrm{PSE}}(v))\,z(v) + (1-\rho)\sum_{w<l_{\mathrm{PSE}}(w)}\frac{1}{n}\,(w - l_{\mathrm{PSE}}(w)) + \delta_{\mathrm{PSE}}.
$$

From the chosen parameter $\delta_{\text{PSE}} = 991$, the sum of the two terms on the right side is positive. Since $(v - l_{\text{PSE}}(v))\, z(v) \geq 0$, we obtain $U^z(v) > 0$, contradicting $U^z(v) \leq 0$. $\square$

Lemma A9. *PSE has a unique ME equilibrium. The ME opt-out strategy z has a threshold $v^k < l_{\text{PSE}}(v^k)$ such that $z(v) = 1$ if $v < v^k$ and $z(v) = 0$ otherwise.*

Proof of Lemma A9. First, we construct an equilibrium z. For any threshold $v^k \in V$, define $z(v) = 1$ if $v < v^k$ and $z(v) = 0$ otherwise. Among the thresholds for which the resulting strategy satisfies $U^z(v) \leq 0$ for every $v < v^k$ and $U^z(v) > 0$ for every $v \geq v^k$, choose the highest one. At least one such threshold exists: if $v^k = v^1$, then $z(v) = 0$ and $U^z(v) = \delta_{\text{PSE}} > 0$ for every $v \in V$. By construction, z is an equilibrium. Lemma A8 implies $v < l_{\text{PSE}}(v)$ for every $v < v^k$. Indeed, for the present parameters, direct computation gives $v^k < l_{\text{PSE}}(v^k)$.

Next, we show that z is the unique ME equilibrium. Fix any other equilibrium z'. Lemma A8 implies that $z'(v) = z(v) = 0$ for every $v > l_{\text{PSE}}(v)$. Let v^m be the lowest value in V such that $z'(v) = 0$ for every $v \geq v^m$.

To derive a contradiction, suppose that $v^k < v^m$. Define an opt-out strategy z'' by $z''(v) = 1$ if $v < v^m$ and $z''(v) = 0$ if $v \geq v^m$. Equation (A3) then implies

$$U^{z''}(v^1) < \cdots < U^{z''}(v^{m-1}) \leq U^{z'}(v^{m-1}) \leq 0,$$

where the last inequality follows from $z'(v^{m-1}) > 0$. Equation (A3) also implies

$$\begin{aligned} U^{z''}(v^m) = U^{z''}(v^{m+1}) = \cdots = U^{z''}(v^n) &= (1-\rho) \sum_{w \leq v^{m-1}} \frac{1}{n} (w - l_{\text{PSE}}(w)) + \delta_{\text{PSE}} \\ &\geq (1-\rho) \sum_{w \leq l_{\text{PSE}}(w)} \frac{1}{n} (w - l_{\text{PSE}}(w)) + \delta_{\text{PSE}}. \end{aligned}$$

Direct computation shows that the last term is positive. Thus, z'' is an equilibrium with a threshold $v^m > v^k$, contradicting the construction of z. Hence, $v^k \geq v^m$. It follows that $z(v) \geq z''(v) \geq z'(v)$ for every $v \in V$. Thus, z is the unique ME equilibrium. $\square$

Proof of Proposition 2. The proof follows from Lemmas A5–A7 and A9. The result for the entry strategy y follows from $y(v) = 1 - z(v)$. $\square$

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Online Supplemental Material for "Entry and Bidding Behavior in Surplus-Extracting Auctions: An Experiment"

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This Supplemental Material is organized as follows. Section A presents English translations of the experimental instructions for the full-surplus-extracting (FSE) treatment. Sections B and C contain supplementary material for Sections II and III of the main paper, respectively. Section D collects supplementary lemmas supporting the theoretical results in the main paper.

A Instructions for FSE treatment

General rules

We will now explain the rules of the experiment. This experiment involves an "auction." Participants will play an "auction game" with others under the experimental rules. The experiment will be conducted on a website. Items being auctioned are hypothetical. Each auction involves two bidders competing in pairs.

You will receive monetary rewards based on the experimental results. The initial reward is 3,000 yen, and the reward amount will increase or decrease depending on the results. Profits and losses within the game are referred to as "points."

Rules for each auction round

At the start of each round, the "values" of the auctioned item for bidders are determined stochastically. A winning bidder earns points based on the value of the item. Values range from 100 to 10,000 points in increments of 100 points. The probability of each combination of two bidders' values is shown on the next page.

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In the table,[1] the values for Bidder A are listed on the left while those for Bidder B are listed at the top. Some parts of the table are omitted. Each diagonal cell has a probability of 51 out of 15,000, while all other cells have a probability of 1 out of 15,000. This indicates that it is relatively more likely that both bidders have the same value. For instance, the probability of both bidders having a value of 100 is 51 out of 15,000, whereas the probability of Bidder A having a value of 100 and Bidder B having a value of 10,000 is 1 out of 15,000. The sum of the probabilities across all cells is 1, or 100%.

You are informed of your own value but not your opponent's value. You then decide whether to enter the auction and, if you do, how much to bid. Bids can range from 100 to 10,000 points in increments of 100 points. If you choose to opt out, your bid is recorded as 0 points, and you will earn no profit.

After both bidders submit their bids, the price rises automatically from 0 points and stops at the lower of the two bids. This is the "auction price." The bidder who submitted the higher bid becomes the "winner." If both bidders submit the same bid, the winner is randomly determined. If both bidders choose to opt out, no winner is declared. The winner earns a "profit from winning," calculated by subtracting the auction price from their value.

Finally, if both bidders enter the auction, your profit is further adjusted depending on your opponent's bid, regardless of your own bid or whether you won the auction. The adjustment is calculated using the following formula:

$$\text{Your profit adjustment} = 2223 - \frac{\text{Opponent's bid}}{100} \times \left(\frac{\text{Opponent's bid}}{100} - 1 \right).$$

Although this formula may seem complex, you can refer to it during the experiment. However, if either you or your opponent opts out, this adjustment will be 0 points.

Additionally, the profit adjustment is represented graphically.[2] The horizontal axis represents your opponent's bid, and the vertical axis shows the corresponding profit adjustment for you. As shown, higher bids by your opponent result in fewer points for you. You can refer to this graph during the experiment.

Groups and competing pairs

Participants are randomly assigned to groups of six at the start of the experiment, and these groups remain fixed throughout the experiment. If the total number of participants is insufficient, computer bidders will be added to form groups of six. Participants will be informed if computer bidders are present in their group. If they are present, the bidding behavior will be displayed on the screen. Participants play 20 rounds of auction games. For each round, pairs are randomly formed within the group.

[1] The table is presented in Figure B1.

[2] The figure is shown by Figure B3.

Rewards from the auction

For each participant, one of the 20 rounds will be randomly selected to determine their reward. The total profit from the selected round is multiplied by 0.1 to calculate a performance-based reward, which can be negative. The fractions are rounded up. Additionally, each participant receives an initial reward of 3,000 yen. The final auction reward is the sum of the performance-based reward and the initial reward. The selected reward-determining round is not revealed until the end of the experiment; therefore, you should make decisions carefully in all rounds.

Screens for each auction round

Each auction round consists of two screens.

1. Bidding screen:[3]

   The top-left side of the page displays the time limit. After the time expires, the system automatically moves to the next page. The page title indicates that this is the third auction round. Below, you can see whether this round is the reward-determining round for your opponent; however, you will not know if it is your own until the experiment concludes. You can also check your value in this round. In this example, your value is 9,000 points. Using the provided tools (radio buttons and a slider), you choose whether to enter and, if so, how much to bid. Once the time limit expires, your choice will be automatically submitted. You can adjust your choices until this point.

   There is more to the bidding screen. By clicking on this menu, you can check the results of previous rounds, the experimental rules, and the profit adjustment rule.

2. Auction result screen:[4]

   The price rises from 0 points in an animation, stopping at the lower of the two bids. This is the auction price. In this example, your bid is 5,000 points, and your opponent's bid is 4,000 points; thus, the auction price is 4,000 points. Since you submitted the higher bid, you win. Profit is calculated by subtracting the auction price (4,000 points) from your value (9,000 points), resulting in a profit of 5,000 points. Additionally, your profit increases by 663 points based on your opponent's bid under the profit adjustment rule. As a result, your total profit in this round is 5,663 points—the sum of your profit and the profit adjustment.

Schedule

[3]This decision screen is presented in Figure B2.
[4]This feedback screen is presented in Figure B4.

The experiment consists of the following steps:

1. Logging into the website;
2. Completing a trait questionnaire;
3. Participating in two practice rounds of auctions;
4. Taking a comprehension quiz on the rules;
5. Completing 20 rounds of auctions;
6. Taking a quiz unrelated to the auction;
7. Completing a brief survey and receiving payment.

This concludes the explanation of the experimental rules.

B Supplementary material for Section II

B.1 Quiz questions on experimental rules for FSE

1. Please select <u>all correct statements</u> about how groups and auction pairs are determined.

- After the experiment begins, each participant is randomly assigned to a group of six.
- In each auction round, each participant is randomly assigned to a group of six.
- Within each group, auction pairs are randomly formed every five rounds.
- Within each group, auction pairs are randomly formed in every round.

2. Please answer each of the following questions about the rules of the auction in each round.

Suppose your value is 7,000 points.

What is the probability that your opponent's value is also 7,000 points?

- 1/2
- 51/150
- 1/100
- 1/150

Suppose your value is 7,000 points.

What is the probability that your opponent's value is 1,000 points?

- 1/2
- 51/150
- 1/100
- 1/150

3. Suppose that your value is 7,000 points, your bid is 9,000 points, and your opponent's bid is 3,000 points.

What is the "auction price" in this case?

- 9,000
- 7,000
- 3,000
- 0

What is your "profit from winning"?

- 4,000
- 2,000
- 0
- −2,000

What is your "profit adjustment"?

(See the profit-adjustment rule at the bottom of the page.)

- 2,223
- 1,353
- 0
- −5,787

4. Suppose that your value is 7,000 points, your bid is 9,000 points, and your opponent's bid is 0 (does not participate).

What is the "auction price" in this case?

- 9,000
- 7,000
- 3,000
- 0

What is your "profit from winning"?

- 9,000
- 7,000
- 3,000
- 0

What is your "profit adjustment"?

(See the profit-adjustment rule at the bottom of the page.)

- 2,223
- 1,353
- 0
- −5,787

5. Please select <u>all correct statements</u> about payments from the auctions.

- For each participant, one payment round is randomly selected from the 20 auction rounds.
- The performance-based payment from the auctions (in yen) is determined as $0.1\times$ the total profit (in points) in the payment round, rounded up to the nearest yen.
- In each auction round, participants are not informed at that time whether the round is their own payment round.
- In each auction round, participants are not informed at that time whether the round is their opponent's payment round.

B.2 Supplementary figures and tables

Bidder B's value

Bidder A's value	100	200	$\cdots$	9900	10000	Total
100	$\frac{51}{15000}$	$\frac{1}{15000}$	$\cdots$	$\frac{1}{15000}$	$\frac{1}{15000}$	$\frac{1}{100}$
200	$\frac{1}{15000}$	$\frac{51}{15000}$	$\cdots$	$\frac{1}{15000}$	$\frac{1}{15000}$	$\frac{1}{100}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
9900	$\frac{1}{15000}$	$\frac{1}{15000}$	$\cdots$	$\frac{51}{15000}$	$\frac{1}{15000}$	$\frac{1}{100}$
10000	$\frac{1}{15000}$	$\frac{1}{15000}$	$\cdots$	$\frac{1}{15000}$	$\frac{51}{15000}$	$\frac{1}{100}$
Total	$\frac{1}{100}$	$\frac{1}{100}$	$\cdots$	$\frac{1}{100}$	$\frac{1}{100}$	1

Figure B1: Joint value distribution.

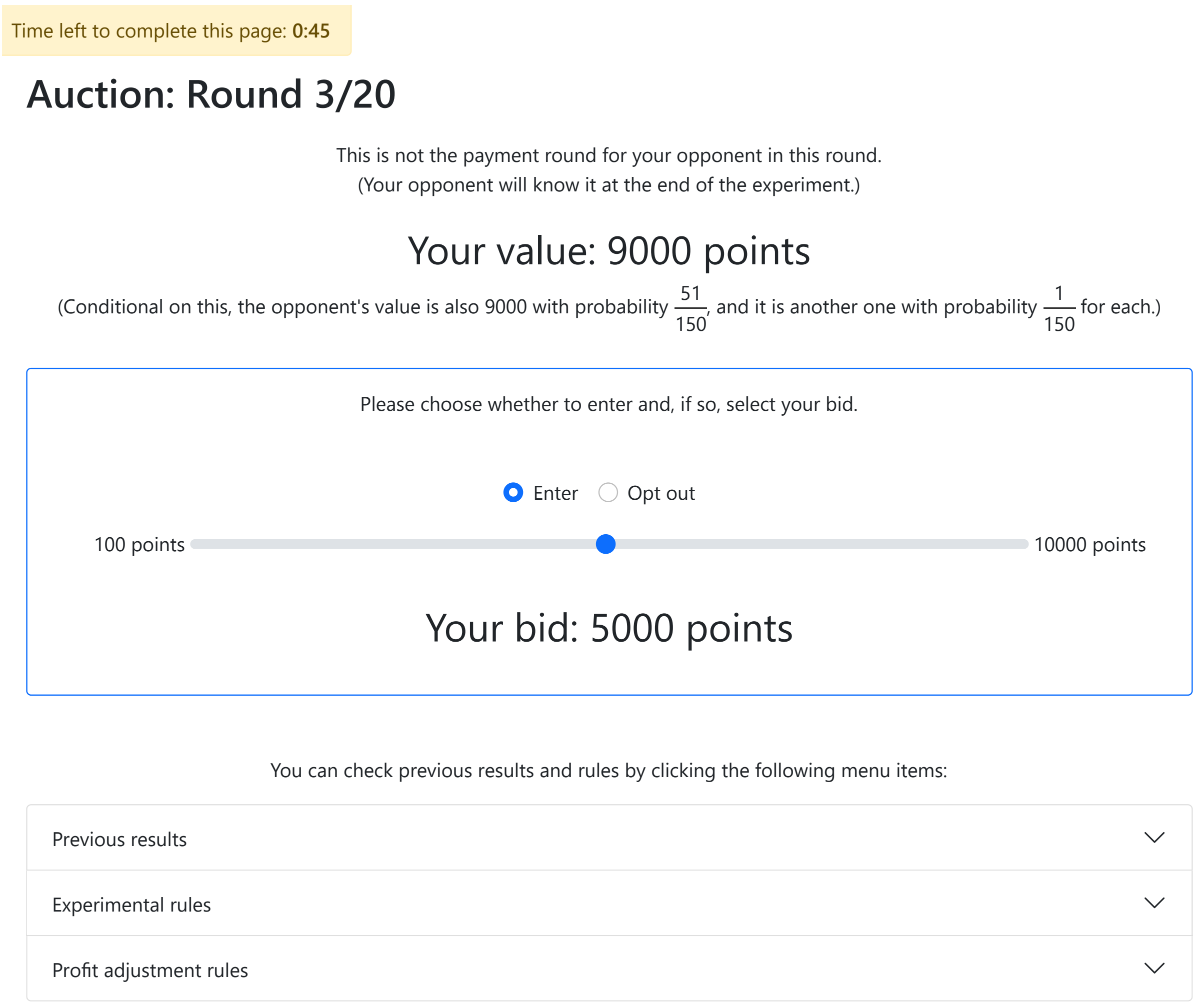


Figure B2: Screenshot of the decision screen.

Notes: When a participant chose to opt out, the bid slider was disabled and grayed out. The default bid was set to 5000 points, and bids were restricted to 100-point increments. The current decision was automatically submitted after 45 seconds. Under the amended random-payment scheme, each participant was informed whether the current round was the payment round for their opponent. In the experiment, all captions on this page were displayed in Japanese.

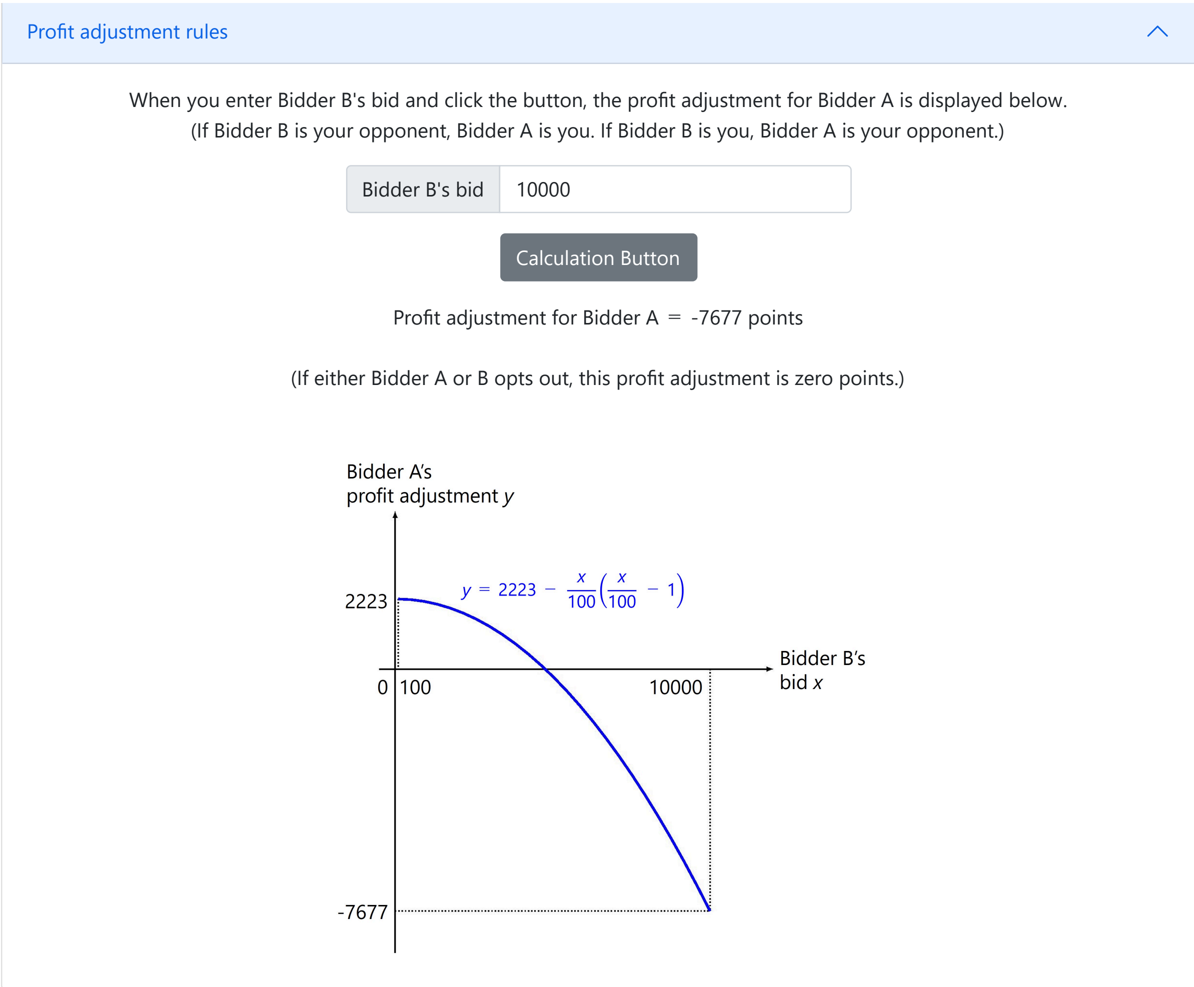


Figure B3: Profit-adjustment (lottery) rule.

Notes: In the 2P treatment, the profit adjustment rule was not provided. In the experiment, all captions on this page were displayed in Japanese.

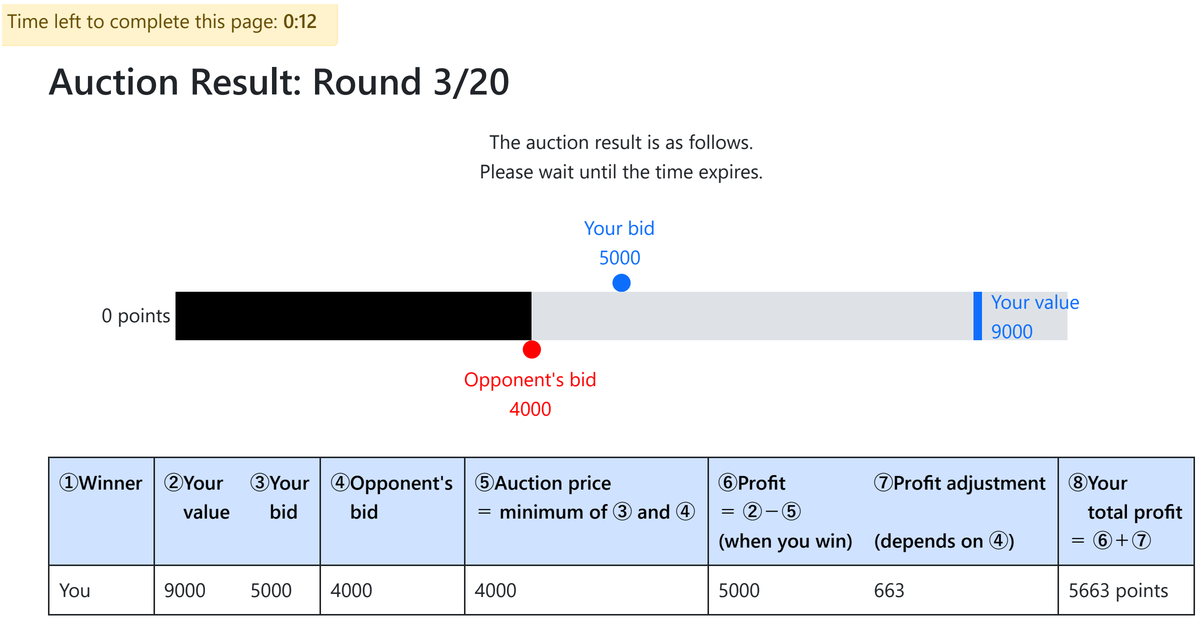


Figure B4: Screenshot of the feedback screen.

Notes: Under the ascending-clock presentation, the black bar extended from zero to the lower of the two bids. Subjects were required to wait for 15 seconds. In the 2P treatment, the last two columns (profit adjustment and total profit) were not displayed. In the experiment, all captions on this page were displayed in Japanese.

Table B1: Multiple Price Lists (MPL) for the elicitation of risk attitudes.

Gain domain

Problem	Lottery A (safe)				Lottery B (risky)			
	Prob.	Payoff	Prob.	Payoff	Prob.	Payoff	Prob.	Payoff
1	10%	200	90%	160	10%	385	90%	10
2	20%	200	80%	160	20%	385	80%	10
3	30%	200	70%	160	30%	385	70%	10
4	40%	200	60%	160	40%	385	60%	10
5	50%	200	50%	160	50%	385	50%	10
6	60%	200	40%	160	60%	385	40%	10
7	70%	200	30%	160	70%	385	30%	10
8	80%	200	20%	160	80%	385	20%	10
9	90%	200	10%	160	90%	385	10%	10
10	100%	200	0%	160	100%	385	0%	10

Loss domain

Problem	Lottery A (safe)				Lottery B (risky)			
	Prob.	Payoff	Prob.	Payoff	Prob.	Payoff	Prob.	Payoff
1	10%	−200	90%	−160	10%	−385	90%	−10
2	20%	−200	80%	−160	20%	−385	80%	−10
3	30%	−200	70%	−160	30%	−385	70%	−10
4	40%	−200	60%	−160	40%	−385	60%	−10
5	50%	−200	50%	−160	50%	−385	50%	−10
6	60%	−200	40%	−160	60%	−385	40%	−10
7	70%	−200	30%	−160	70%	−385	30%	−10
8	80%	−200	20%	−160	80%	−385	20%	−10
9	90%	−200	10%	−160	90%	−385	10%	−10
10	100%	−200	0%	−160	100%	−385	0%	−10

Notes: Each participant selected either lottery A or lottery B for all problems in both the gain and loss domains within 3×2 minutes. The order of the domains was randomized across subjects. At the end of the session, one problem from each domain was randomly selected, and the chosen lottery for that problem was resolved by a computer. The payoff is measured in JPY.

In the gain domain, 93% (FSE), 95% (PSE), and 92% (2P) of subjects made at most one switch between the lotteries. In the loss domain, 95% (FSE), 97% (PSE), and 95% (2P) did so. No participant made a dominated choice in the final problem in either domain.

Table B2: Questions included in the Cognitive Reflection Test (CRT).

	Question	Answer
1	A book and a pen cost 1,100 yen in total. The book costs 1,000 yen more than the pen. How much does the pen cost?	50 yen
2	If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?	5 minutes
3	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?	47 days
4	If Taro can drink one barrel of water in 6 days, and Hanako can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together?	4 days
5	Jiro received both the 15th highest and the 15th lowest mark in the class. How many students are in the class?	29 students
6	A man buys a pig for 6,000 yen, sells it for 7,000 yen, buys it back for 8,000 yen, and sells it finally for 9,000 yen. How much has he made?	2,000 yen
7	Saburo decided to invest 800,000 yen in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Saburo, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Saburo has: a. broken even in the stock market, b. is ahead of where he began, c. has lost money.	c

Notes: Each participant answered all questions within 6 minutes, earning JPY 60 for each correct answer. In the experiment, the questions were displayed in Japanese. For the Japanese version of this CRT, see Harada, Harada and Suto (2018).

Table B3: Sessions.

Treatment	Session	Date	Number of groups	Number of subjects	University
FSE	1	January 23, 2023	2	12	Osaka
	2	January 24, 2023	4	24	Osaka
	3	January 24, 2023	3	18	Osaka
	4	March 7, 2023	3	18 (22)	Osaka
	5	January 26, 2023	4	24 (25)	Kansai
	6	January 26, 2023	4	24	Kansai
	7	January 30, 2023	3	18 (23)	Kansai
	8	January 30, 2023	4	24	Kansai
PSE	1	January 23, 2023	2	12 (15)	Osaka
	2	January 25, 2023	2	12 (17)	Osaka
	3	March 6, 2023	3	18 (22)	Osaka
	7	January 27, 2023	4	24 (25)	Kansai
	8	January 27, 2023	3	18 (22)	Kansai
2P	1	January 26, 2023	3	18 (20)	Osaka
	2	January 26, 2023	2	12 (16)	Osaka
	3	March 6, 2023	3	18 (22)	Osaka
	7	January 27, 2023	2	12	Kansai
	8	January 30, 2023	4	24	Kansai

Notes: This table presents the date, the numbers of (human-only) groups and subjects, and the university for each session. The numbers of subjects in parentheses include those who participated in groups with computerized bidders. The two sessions affected by technical issues during the instruction phase, as noted in footnote 27 of the main paper, correspond to Sessions 5 and 6 for FSE.

Table B4: Characteristics.

		FSE	PSE	2P	FSE vs. PSE	FSE vs. 2P	PSE vs. 2P
Gender	Male	45.6%	45.2%	57.1%			
	Female	47.5%	51.1%	38.0%			
	Other	2.4%	0%	3.5%			
	No answer	4.3%	3.5%	1.1%			
Age		21.4	21.5	21.2	0.610	0.702	0.457
Number of safe choices (gain)		5.7	5.9	5.7	0.591	0.902	0.510
Number of safe choices (loss)		6.0	5.8	5.8	0.372	0.652	0.735
CRT score		5.3	5.2	5.5	0.450	0.355	0.120
Number of mistakes in quiz		4.0	4.2	3.5	0.975	0.011	0.026

Notes: This table summarizes the treatment characteristics. For each treatment, it details the gender composition as well as the averages for age, number of safe choices in the MPL task, CRT score, and cumulative total mistakes in the comprehension quiz. The last three columns report the p-values from the Wilcoxon rank-sum tests that compare each pair of treatments.

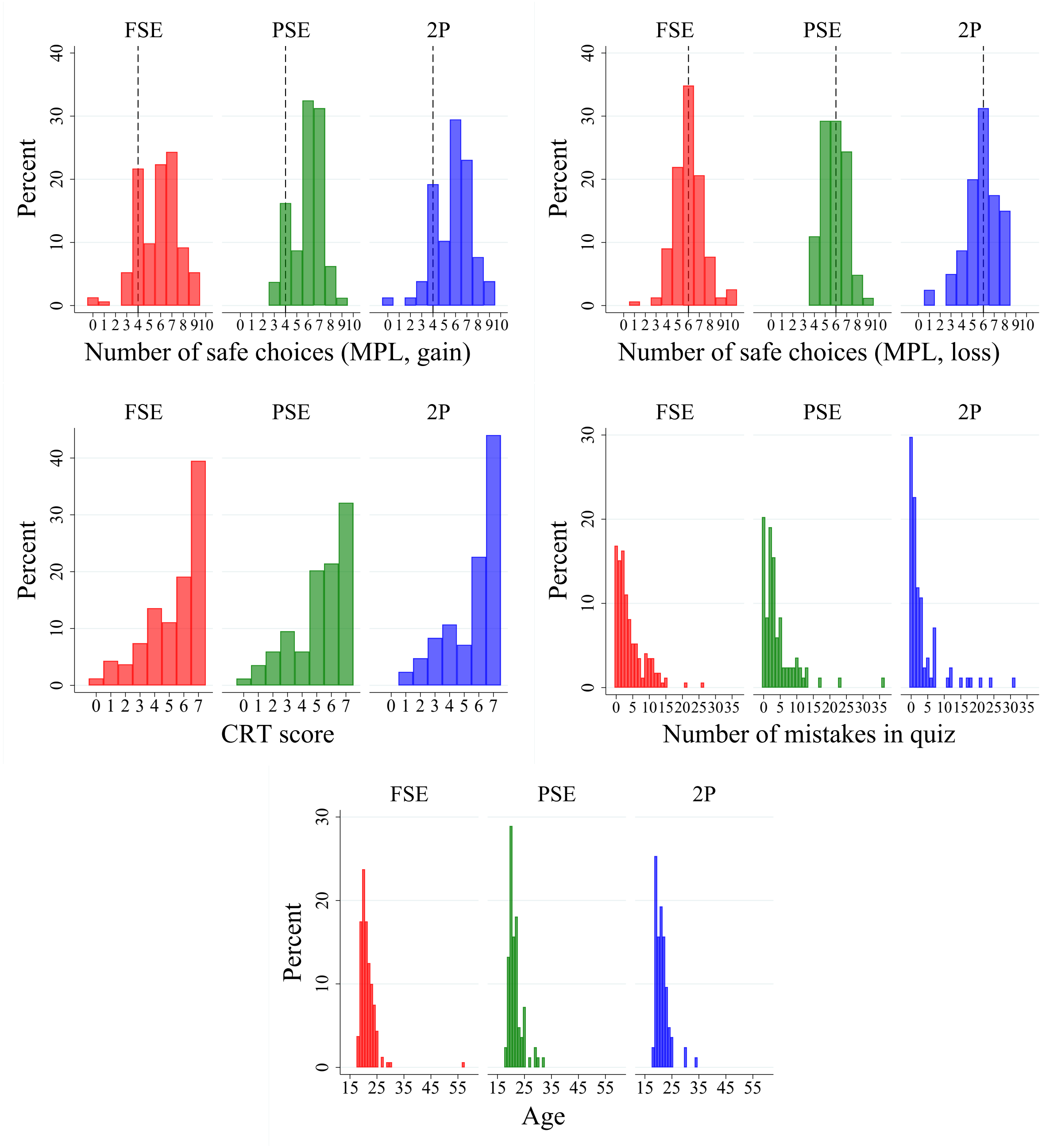


Figure B5: Histograms of the subjects' characteristics.

Notes: In the MPL histograms, the dashed lines indicate the number of safe lotteries chosen by a risk-neutral decision maker: four in the gain domain and six in the loss domain, respectively.

C Supplementary material for Section III

C.1 Recent opponent behavior and current entry decisions

This subsection examines the robustness of the results on entry decisions by using a longer history of opponent behavior. Specifically, Panels A and B of Table C1 replace the previous opponent's bid and entry indicator with the mean opponent bid and opponent entry rate over the previous two and three rounds, respectively. The top panel reproduces the corresponding estimates from the main analysis for comparison. The main patterns remain qualitatively similar: higher recent opponent bids are generally associated with lower current entry in FSE and PSE, whereas no corresponding negative relationship is observed in 2P.

Table C1: Treatment-specific associations between recent opponent behavior and current entry.

		First 10 rounds	Last 10 rounds
Main paper: Previous round			
Previous opponent's bid / 1000	FSE	-0.007 (0.004)	-0.013^{***} (0.003)
	PSE	-0.010^{**} (0.003)	-0.012^{*} (0.005)
	2P	0.000 (0.001)	0.002 (0.001)
Previous opponent entered	FSE	0.008 (0.027)	0.066^{*} (0.031)
	PSE	0.111^{*} (0.047)	0.061 (0.038)
	2P	0.005 (0.034)	0.018 (0.036)
Panel A: Previous two rounds			
Mean opponent bid / 1000	FSE	-0.014^{**} (0.005)	-0.017^{**} (0.006)
	PSE	-0.021^{***} (0.005)	-0.011 (0.009)
	2P	0.002 (0.002)	0.005 (0.002)
Opponent entry rate	FSE	0.047 (0.042)	0.032 (0.048)
	PSE	0.170^{**} (0.063)	0.022 (0.079)
	2P	-0.002 (0.015)	-0.006 (0.031)
Panel B: Previous three rounds			
Mean opponent bid / 1000	FSE	-0.019^{**} (0.005)	-0.024^{**} (0.008)
	PSE	-0.027^{***} (0.006)	-0.014 (0.014)
	2P	0.001 (0.003)	0.006^{*} (0.003)
Opponent entry rate	FSE	0.042 (0.049)	0.059 (0.063)
	PSE	0.215^{**} (0.078)	0.074 (0.114)
	2P	0.010 (0.031)	-0.001 (0.061)

Notes: The first panel reproduces treatment-specific estimates from Table 2 in the main paper. Panels A and B report corresponding treatment-specific linear combinations of coefficients from Table C2. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table C2: Mixed-effects linear probability models for entry decisions using recent opponent behavior.

Panel A: Mean opponent behavior in the previous two rounds

Dependent variable	Entry	
	First 10 rounds	Last 10 rounds
(Constant)	0.607^{***}	0.507^{***}
	(0.040)	(0.044)
PSE	0.061	0.193
	(0.069)	(0.099)
2P	0.280^{***}	0.341^{***}
	(0.053)	(0.075)
Round	-0.008^{*}	-0.003
	(0.003)	(0.002)
PSE × Round	-0.005	-0.004
	(0.005)	(0.005)
2P × Round	0.007	0.006
	(0.004)	(0.003)
Value / 1000	0.050^{***}	0.058^{***}
	(0.004)	(0.004)
PSE × Value / 1000	-0.007	-0.011
	(0.008)	(0.009)
2P × Value / 1000	-0.036^{***}	-0.046^{***}
	(0.006)	(0.005)
Mean opponent bid in the previous two rounds / 1000	-0.014^{**}	-0.017^{**}
	(0.005)	(0.006)
PSE × Mean opponent bid in the previous two rounds / 1000	-0.006	0.005
	(0.007)	(0.010)
2P × Mean opponent bid in the previous two rounds / 1000	0.016^{**}	0.022^{**}
	(0.005)	(0.006)
Opponent entry rate in the previous two rounds	0.047	0.032
	(0.042)	(0.048)
PSE × Opponent entry rate in the previous two rounds	0.123	-0.010
	(0.075)	(0.093)
2P × Opponent entry rate in the previous two rounds	-0.049	-0.038
	(0.045)	(0.058)
Observations	2,740	3,082

Table C2: Mixed-effects linear probability models for entry decisions using recent opponent behavior (continued).

Panel B: Mean opponent behavior in the previous three rounds

Dependent variable	Entry	
	First 10 rounds	Last 10 rounds
(Constant)	0.631^{***}	0.523^{***}
	(0.049)	(0.043)
PSE	0.019	0.153
	(0.090)	(0.122)
2P	0.249^{***}	0.316^{***}
	(0.062)	(0.090)
Round	-0.007^{*}	-0.003
	(0.003)	(0.002)
PSE × Round	-0.004	-0.004
	(0.005)	(0.005)
2P × Round	0.007	0.006
	(0.004)	(0.003)
Value / 1000	0.050^{***}	0.058^{***}
	(0.004)	(0.004)
PSE × Value / 1000	-0.006	-0.011
	(0.008)	(0.009)
2P × Value / 1000	-0.036^{***}	-0.046^{***}
	(0.006)	(0.005)
Mean opponent bid in the previous three rounds / 1000	-0.019^{**}	-0.024^{**}
	(0.005)	(0.008)
PSE × Mean opponent bid in the previous three rounds / 1000	-0.008	0.009
	(0.008)	(0.017)
2P × Mean opponent bid in the previous three rounds / 1000	0.020^{**}	0.030^{***}
	(0.006)	(0.008)
Opponent entry rate in the previous three rounds	0.042	0.059
	(0.049)	(0.063)
PSE × Opponent entry rate in the previous three rounds	0.173	0.015
	(0.093)	(0.130)
2P × Opponent entry rate in the previous three rounds	-0.031	-0.060
	(0.059)	(0.088)
Observations	2,740	3,082

Notes: The dependent variable is $\mathbf{1}\{b_{it} > 0\}$, where $\mathbf{1}\{\cdot\}$ is the indicator function. FSE is the reference treatment. The mean variables are calculated from available observations over the previous two or three rounds, depending on the panel; therefore, round 1 is excluded. All models include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

C.2 Risk aversion and the minimum-entry equilibrium

This subsection examines how symmetric equilibrium behavior changes with bidders' risk attitudes, starting from the minimum-entry (ME) equilibria established by Proposition 2 in the main paper. We assume that bidders have a constant-absolute-risk-aversion (CARA) utility function u over monetary payoff x:

$$u(x) = \frac{1 - \exp(-ax)}{a}$$

for $a \neq 0$, and $u(x) = x$ for $a = 0$. We set $x = 0.1 \times$ profit to express auction profits in the same monetary units as the MPL payoffs. Table C3 reports the ranges of the CARA parameter a implied by the number of safe choices in the MPL.

Table C3: CARA parameter ranges implied by MPL choices.

Number of safe choices	Implied range of CARA parameter a	
	Gain domain	Loss domain
0	$a < -0.0093$	NA (not rationalizable)
1	$-0.0093 < a < -0.0055$	$a < -0.0119$
2	$-0.0055 < a < -0.0030$	$-0.0119 < a < -0.0078$
3	$-0.0030 < a < -0.0009$	$-0.0078 < a < -0.0051$
4	$-0.0009 < a < 0.0010$	$-0.0051 < a < -0.0029$
5	$0.0010 < a < 0.0029$	$-0.0029 < a < -0.0010$
6	$0.0029 < a < 0.0051$	$-0.0010 < a < 0.0009$
7	$0.0051 < a < 0.0078$	$0.0009 < a < 0.0030$
8	$0.0078 < a < 0.0119$	$0.0030 < a < 0.0055$
9	$0.0119 < a$	$0.0055 < a < 0.0093$
10	NA (not rationalizable)	$0.0093 < a$

Notes: This table reports the ranges of the CARA parameter a implied by the number of safe choices for a decision maker who switches between lotteries at most once in the MPL. Positive values of a indicate risk aversion, $a = 0$ risk neutrality, and negative values risk seeking.

We first note that Lemma A3 in the main paper continues to hold for any value of a, so bidders bid their values conditional on entry in any symmetric equilibrium. We can therefore represent any symmetric equilibrium as an entry strategy, as in the main paper. Starting from the risk-neutral ME equilibrium at $a = 0$, we vary a in small increments and numerically search for a symmetric equilibrium entry strategy, using the equilibrium obtained at the previous step as the initial guess. Figures C1 and C2 illustrate the resulting symmetric equilibria for FSE and PSE, respectively. In both auctions, higher values of the CARA parameter a reduce equilibrium entry, particularly for bidders with high values. Table C4 summarizes the corresponding ex ante entry probabilities.

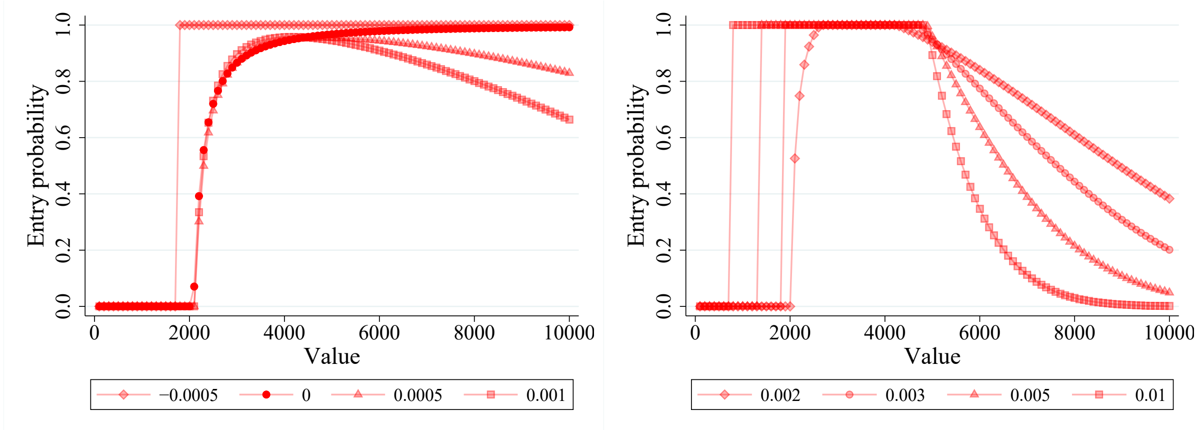


Figure C1: Symmetric equilibrium entry strategies in the FSE auction.

Notes: Each curve shows the equilibrium entry probability as a function of value for a given CARA parameter a. The left and right panels display different ranges of a for readability.

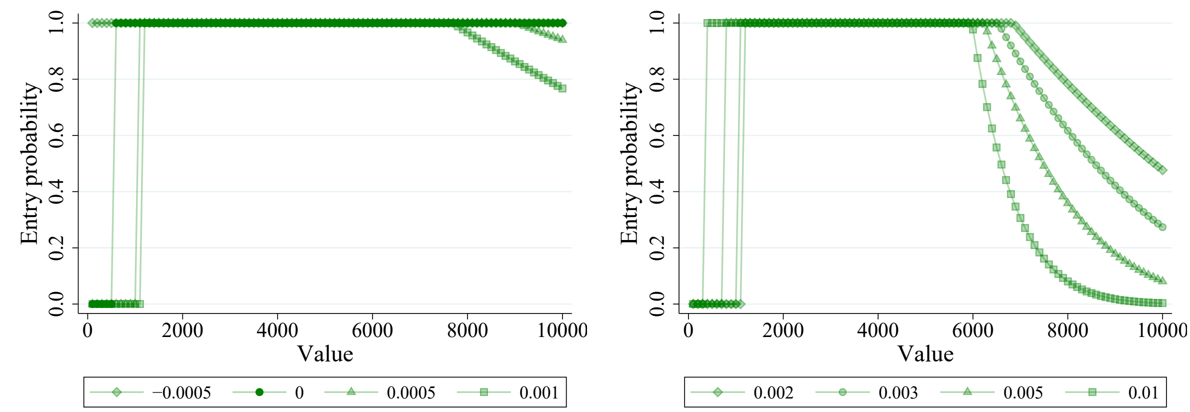


Figure C2: Symmetric equilibrium entry strategies in the PSE auction.

Notes: The notes for Figure C1 apply here.

Table C4: Ex ante entry probabilities for the reported equilibria.

CARA parameter a	Entry probability	
	FSE	PSE
−0.0005	0.83	1.00
0	0.74	0.95
0.0005	0.70	0.89
0.001	0.66	0.86
0.002	0.61	0.79
0.003	0.58	0.75
0.005	0.54	0.69
0.01	0.51	0.64

Notes: The table reports ex ante entry probabilities for the symmetric equilibria obtained numerically as the CARA parameter a varies, using the risk-neutral ME equilibrium at $a = 0$ as the starting point.

C.3 Recent opponent behavior and current bidding behavior

This subsection examines the robustness of the results on entrants' bidding behavior by using a longer history of opponent behavior. Specifically, Panels A and B of Table C5 replace the previous opponent's bid and entry indicator with the mean opponent bid and opponent entry rate over the previous two and three rounds, respectively. The top panel reproduces the corresponding estimates from the main analysis for comparison. The main patterns remain qualitatively similar. In the first 10 rounds, higher recent opponent bids are associated with larger current deviations from value bidding among entrants in both FSE and PSE. In the last 10 rounds, this positive association remains evident in FSE when longer histories are used, but not in PSE. No corresponding relationship is observed in 2P.

Table C5: Treatment-specific associations between recent opponent behavior and current deviations from value bidding among entrants.

		First 10 rounds	Last 10 rounds
Main paper: Previous round			
Previous opponent's bid / 1000	FSE	104.2*** (16.6)	24.6* (22.8)
	PSE	84.2** (29.9)	34.3 (36.7)
	2P	−10.0 (20.3)	2.9 (11.6)
Previous opponent entered	FSE	−331.8 (204.7)	59.4 (161.2)
	PSE	168.1 (416.5)	−99.2 (325.5)
	2P	328.8 (409.5)	237.7 (261.2)
Panel A: Previous two rounds			
Mean opponent bid / 1000	FSE	136.0*** (25.6)	81.6* (36.0)
	PSE	171.4*** (45.0)	44.4 (51.6)
	2P	−8.8 (32.1)	7.0 (17.1)
Opponent entry rate	FSE	−555.0 (332.6)	−217.5 (255.4)
	PSE	−395.6 (649.6)	−170.6 (592.2)
	2P	831.1 (655.0)	−83.8 (163.9)
Panel B: Previous three rounds			
Mean opponent bid / 1000	FSE	142.7** (37.6)	127.0** (47.0)
	PSE	233.3*** (45.5)	−7.7 (49.3)
	2P	12.3 (40.6)	10.0 (21.4)
Opponent entry rate	FSE	−494.2 (432.1)	−440.6 (313.8)
	PSE	−406.8 (707.1)	−213.5 (668.2)
	2P	1044.9 (731.0)	122.0 (373.9)

Notes: The first panel reproduces treatment-specific estimates from Table 4 in the main paper. Panels A and B report corresponding treatment-specific linear combinations of coefficients from Table C6. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table C6: Mixed-effects linear models for deviations from value bidding among entrants using recent opponent behavior.

Panel A: Mean opponent behavior in the previous two rounds

Dependent variable	Deviation	
	First 10 rounds	Last 10 rounds
(Constant)	1676.9^{***}	1496.6^{**}
	(269.9)	(442.1)
PSE	464.1	1196.2
	(752.2)	(881.9)
2P	-2454.6^{***}	-1731.9^{**}
	(636.6)	(612.1)
Round	31.4	36.7
	(26.4)	(22.0)
PSE × Round	3.3	-70.0^{*}
	(51.6)	(32.7)
2P × Round	19.9	−10.1
	(33.3)	(29.5)
Value / 1000	-321.6^{***}	-289.8^{***}
	(35.4)	(40.4)
PSE × Value / 1000	−92.3	11.5
	(61.6)	(57.2)
2P × Value / 1000	180.6^{***}	241.6^{***}
	(48.0)	(42.8)
Mean opponent bid in the previous two rounds / 1000	136.0^{***}	81.6^{*}
	(25.6)	(36.0)
PSE × Mean opponent bid in the previous two rounds / 1000	35.3	−37.2
	(51.7)	(62.9)
2P × Mean opponent bid in the previous two rounds / 1000	-144.9^{***}	−74.6
	(41.1)	(39.8)
Opponent entry rate in the previous two rounds	−555.0	−217.5
	(332.6)	(255.4)
PSE × Opponent entry rate in the previous two rounds	159.3	46.9
	(729.8)	(645.0)
2P × Opponent entry rate in the previous two rounds	1386.1	133.6
	(734.7)	(303.5)
Observations	2,313	2,436

Table C6: Mixed-effects linear models for deviations from value bidding among entrants using recent opponent behavior (continued).

Panel B: Mean opponent behavior in the previous three rounds

Dependent variable	Deviation	
	First 10 rounds	Last 10 rounds
(Constant)	1589.9***	1435.1**
	(356.7)	(449.4)
PSE	328.2	1624.3
	(807.3)	(1007.1)
2P	−2675.9***	−1796.9*
	(688.7)	(747.7)
Round	33.2	38.1
	(26.7)	(21.8)
PSE × Round	−6.5	−75.2*
	(51.9)	(33.5)
2P × Round	17.9	−10.5
	(32.7)	(29.5)
Value / 1000	−321.2***	−288.9***
	(35.6)	(39.7)
PSE × Value / 1000	−97.1	6.9
	(61.5)	(56.6)
2P × Value / 1000	181.0***	240.0***
	(48.0)	(42.3)
Mean opponent bid in the previous three rounds / 1000	142.7***	127.0**
	(37.6)	(47.0)
PSE × Mean opponent bid in the previous three rounds / 1000	90.5	−134.8*
	(59.1)	(68.1)
2P × Mean opponent bid in the previous three rounds / 1000	−130.4*	−137.1**
	(55.4)	(51.6)
Opponent entry rate in the previous three rounds	−494.2	−440.6
	(432.1)	(313.8)
PSE × Opponent entry rate in the previous three rounds	87.4	227.0
	(828.7)	(738.3)
2P × Opponent entry rate in the previous three rounds	1539.1	562.6
	(849.2)	(488.1)
Observations	2,313	2,436

Notes: The dependent variable is $b_{it} - v_{it}$. The sample is restricted to observations with $b_{it} > 0$. FSE is the reference treatment. The mean variables are calculated from available observations over the previous two or three rounds, depending on the panel; therefore, round 1 is excluded. All models include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

C.4 Clustering

This subsection explores the extent to which subjects exhibit behavior consistent with undominated bidding or close to symmetric-equilibrium benchmarks, and how departures from these benchmarks can be classified. Specifically, we classify subjects into clusters for each treatment using the k-means clustering algorithm (MacQueen 1967; Hastie, Tibshirani and Friedman 2009). Our clustering analysis is based on data from rounds 11–20 in which the opponent is unpaid.

The clustering procedure is as follows. First, we construct a feature vector for each subject. Subject i's feature vector is $(\underline{e}_i, \overline{e}_i, sd_i, ad_i)$, where $\underline{e}_i$ and $\overline{e}_i$ denote the entry rates in rounds with $v_{it} < 2100$ and $v_{it} \geq 2100$, respectively, and sd_i and ad_i denote the mean signed and absolute deviations from value bidding conditional on entry, respectively. The cutoff of 2100 corresponds to the threshold for the ME entry strategy of FSE.[5] We use the same cutoff across treatments to facilitate comparison of the resulting clusters. Second, for each treatment, we apply the k-means algorithm to classify subjects into k clusters by minimizing the within-cluster sum of squared distances. We set $k = 5$.[6]

Figure C3 shows the clustering results for FSE. The numerical cluster labels are assigned ex post to facilitate comparisons across treatments. Cluster 1 comprises subjects who predominantly follow value bidding, although it also includes some overbidding and opting out at low values. Cluster 2 exhibits behavior resembling the ME equilibrium. Cluster 3 resembles Cluster 2 but consists of subjects who enter primarily when their values are relatively high. Cluster 4 comprises subjects who tend to underbid conditional on entry. Finally, Cluster 5 includes subjects who substantially overbid.

Figure C4 shows the clustering results for PSE. Overall, the results are qualitatively similar to those for FSE. Cluster 1 includes subjects who predominantly follow value bidding. Clusters 2 and 3 resemble Clusters 2 and 3 in FSE, respectively. Cluster 4 consists of subjects who enter infrequently. Cluster 5 comprises overbidders, resembling Cluster 5 in FSE.

Figure C5 presents the clustering results for 2P. The pattern is relatively clear-cut: 80% of the subjects (Cluster 1) are characterized primarily by value bidding, 12% (Clusters 2–4) by underbidding, and 8% (Cluster 5) by overbidding. Most subjects in 2P enter in nearly every round during rounds 11–20.

[5] For subjects without draws of $v_{it} < 2100$, we impute $\underline{e}_i$ using their overall entry rates in the observations used for the clustering analysis. For four subjects in FSE who did not enter in these observations, we set $sd_i = ad_i = 0$. Feature vectors are standardized within each treatment so that each dimension has mean zero and unit variance.

[6] Figure C6 presents elbow plots (Hastie, Tibshirani and Friedman 2009) for alternative numbers of clusters. The qualitative features of the clustering results are robust to choices of k around five; we therefore set $k = 5$ for ease of interpretation.

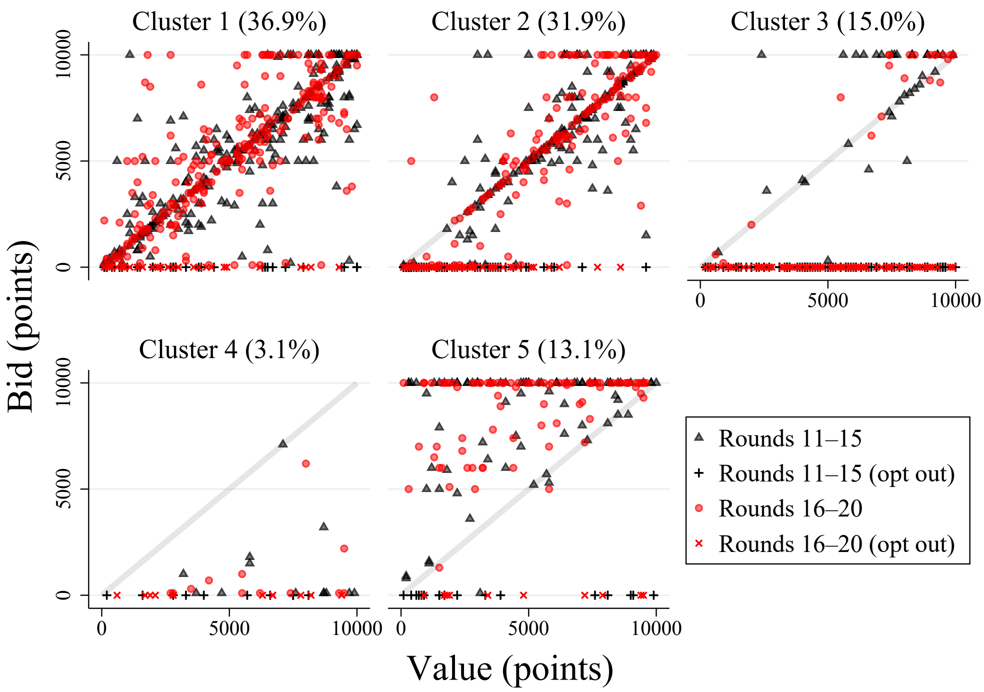


Figure C3: Subject clusters in FSE.

Notes: The percentages in parentheses indicate the proportions of subjects. The solid diagonal line represents value bidding.

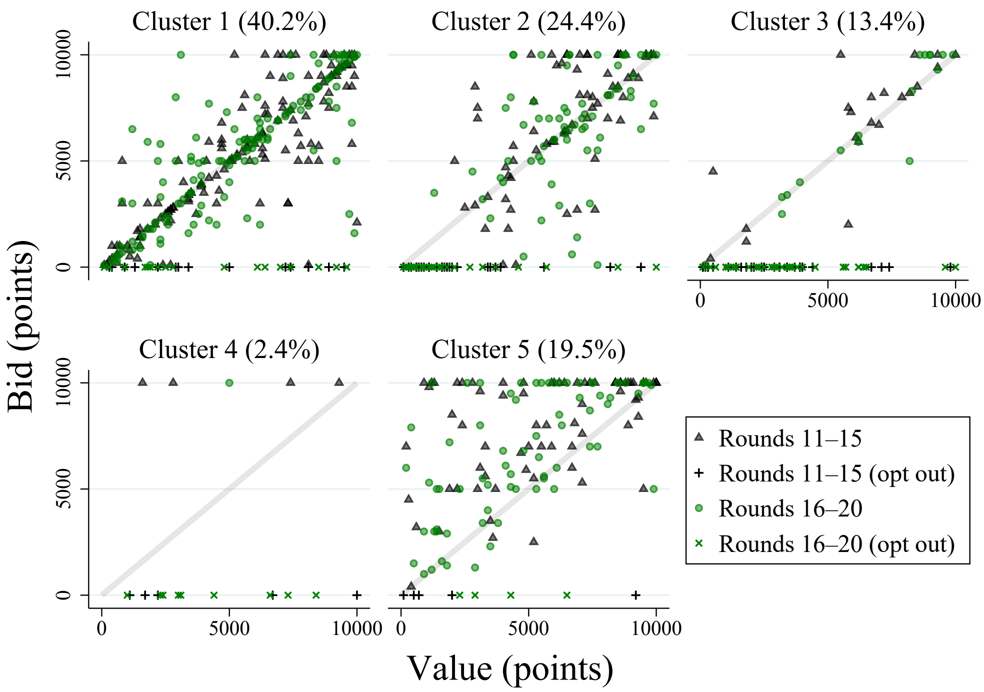


Figure C4: Subject clusters in PSE.

Notes: The notes for Figure C3 apply here.

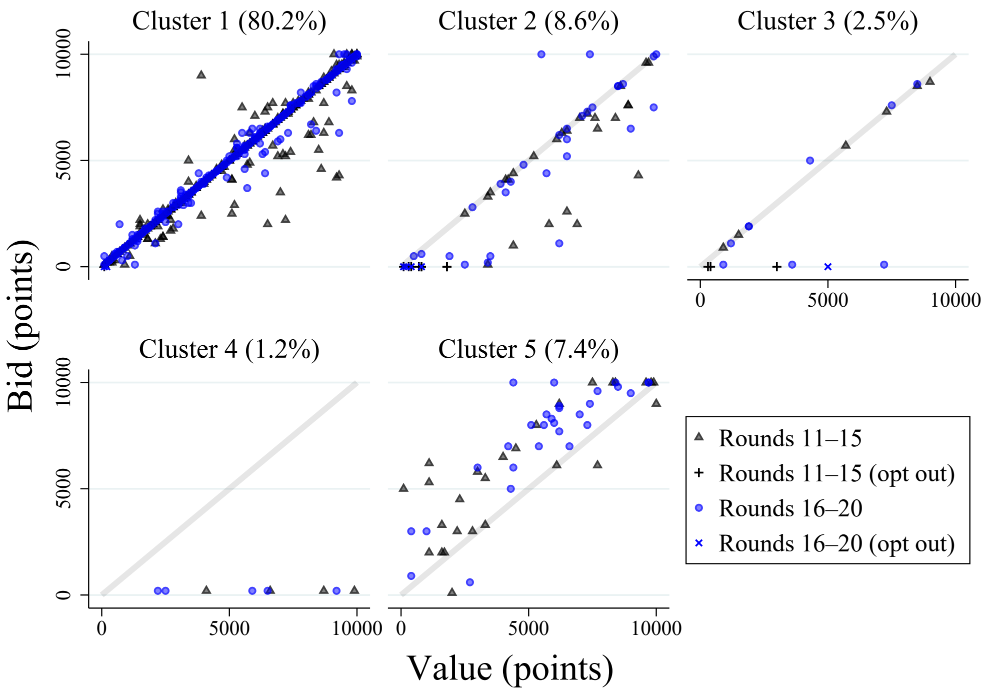


Figure C5: Subject clusters in 2P.

Notes: The notes for Figure C3 apply here.

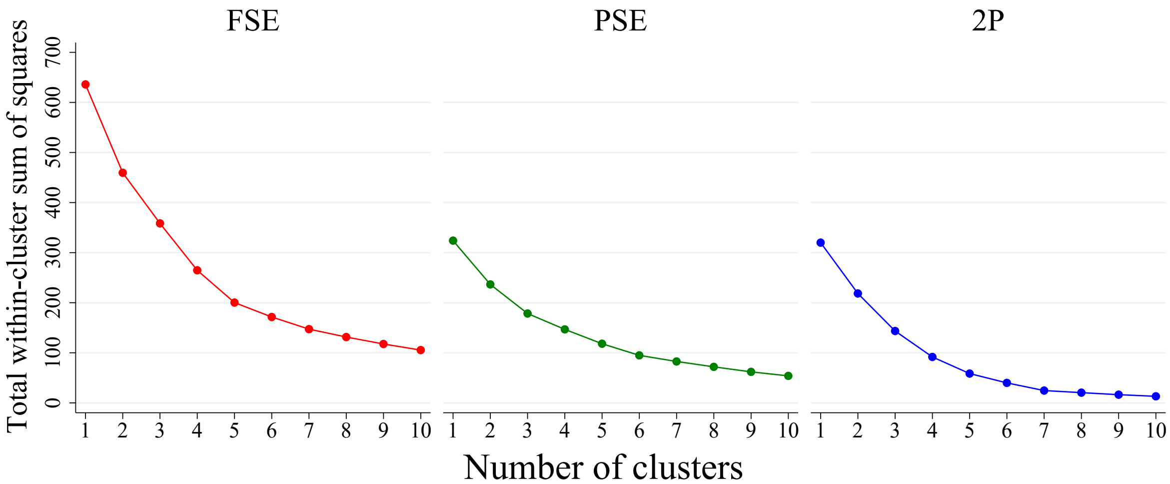


Figure C6: Elbow plots for k-means clustering by treatment.

Notes: The vertical axis reports the total within-cluster sum of squares for each number of clusters.

C.5 Entry responses to systematic overbidding

This subsection explores how the presence of bidders who systematically overbid affects the entry behavior of other bidders. To capture observed bidder behavior, we use a model based on quantal response equilibrium (QRE; McKelvey and Palfrey 1995) in which a fraction of bidders are of an overbidding type. This type is specified as a reduced-form representation of systematic overbidding rather than as a quantal best response. Throughout this subsection, we use data from rounds 11–20 in which the opponent is unpaid.

We construct a heterogeneous QRE-based model (Goeree, Holt and Palfrey 2016, Chapter 4) with two behavioral types: the *baseline type* and the *overbidding type*. Let σ and γ denote the behavioral strategies of the baseline and overbidding types, respectively, as described below, and let $q \in [0,1]$ denote the population share of the overbidding type. An opponent therefore follows the mixture strategy $(1-q)\sigma + q\gamma$. For a baseline-type bidder with value v, the interim expected profit from bidding b against this mixture is denoted by

$$U^{(1-q)\sigma+q\gamma}(v,b).$$

Both types are modeled using a "spike-and-slab" structure, which provides a parsimonious yet flexible representation of behavior. For the baseline type, behavior is governed by a spike-and-slab logit response. Let $\lambda \geq 0$ denote the logit precision parameter governing payoff sensitivity. With probability r, a bidder with value v follows the "spike" component, in which the choice set is restricted to $\{0, v\}$ (opting out or value bidding). Conditional on the spike component, the choice probabilities are given by

$$\sigma_{\mathrm{SP}}(v,b) = \frac{\exp\left[\lambda\, U^{(1-q)\sigma+q\gamma}(v,b)\right]}{\exp\left[\lambda\, U^{(1-q)\sigma+q\gamma}(v,0)\right] + \exp\left[\lambda\, U^{(1-q)\sigma+q\gamma}(v,v)\right]}, \qquad b \in \{0, v\},$$

and $\sigma_{\mathrm{SP}}(v,b) = 0$ for all $b \notin \{0, v\}$. The spike component reflects the dominance of value bidding conditional on entry, while allowing for the separate decision to opt out. With probability $1-r$, the bidder follows the "slab" component, in which the entire bid set B is available. Conditional on the slab component, the choice probabilities follow the standard logit response:

$$\sigma_{\mathrm{SL}}(v,b) = \frac{\exp\left[\lambda\, U^{(1-q)\sigma+q\gamma}(v,b)\right]}{\sum_{b' \in B} \exp\left[\lambda\, U^{(1-q)\sigma+q\gamma}(v,b')\right]}, \qquad b \in B.$$

The baseline-type behavioral strategy is therefore given by

$$\sigma(v,b) = r\, \sigma_{\mathrm{SP}}(v,b) + (1-r)\, \sigma_{\mathrm{SL}}(v,b).$$

To capture the distinctive features of the observed overbidding behavior, the overbidding type is specified as follows. With probability s, a bidder follows the "spike" component $\gamma_{\mathrm{SP}}(b)$ and chooses the maximum bid $b = 10000$ regardless of value v. With probability $1 - s$, the bidder follows the "slab" component $\gamma_{\mathrm{SL}}(v, b)$, which captures systematic overbidding while allowing for occasional noise.[7] The overbidding-type behavioral strategy is therefore given by

$$\gamma(v, b) = s\,\gamma_{\mathrm{SP}}(b) + (1 - s)\,\gamma_{\mathrm{SL}}(v, b).$$

We estimate the model separately for each treatment by conducting a grid search over parameter values to maximize the log-likelihood (LL):[8]

$$LL = \sum_{i \in N} \ln \left[(1 - q) \prod_{t \in T_i} \sigma(v_{it}, b_{it}) + q \prod_{t \in T_i} \gamma(v_{it}, b_{it}) \right], \tag{C1}$$

where N denotes the set of subjects in a given treatment, and $T_i \subset \{11, 12, \ldots, 20\}$ denotes the set of rounds in which subject i's opponent is unpaid. The formulation in (C1) reflects the assumption that each subject's type is fixed across rounds, as in standard finite mixture models (Moffatt 2015). We further assume that, conditional on type and realized values, choices are independent across rounds. For each parameter configuration, the QRE fixed point for the baseline-type strategy σ is computed numerically using the algorithm described at the end of this subsection.

For each treatment, we estimate and compare the six models listed in Table C7, all of which are nested within the unrestricted full model. The most restrictive specification, with $q = r = 0$, corresponds to the standard logit QRE model. The table reports parameter estimates with bootstrap standard errors, estimation LL, AIC, and BIC, as well as validation LL.[9] Across all three treatments, the full model is preferred by both AIC and BIC and also delivers the highest validation LL.

We then classify subjects into behavioral types using their posterior type probabilities (Moffatt 2015, Chapter 8). For this classification, the parameters and behavioral strategies are evaluated at the maximum likelihood estimates of the full model. According to

[7] The slab component is specified as follows. With probability 0.9, a bid is drawn uniformly from the set of admissible bids satisfying $v < b < 10000$; for $v \in \{9900, 10000\}$, the bidder instead bids $b = v$. With probability 0.05, the bidder opts out by submitting $b = 0$, and with probability 0.05, a bid is drawn uniformly from the set of admissible bids satisfying $0 < b < 10000$. The latter two cases capture occasional noise, ensuring that the mixture $s\gamma_{\mathrm{SP}} + (1 - s)\gamma_{\mathrm{SL}}$ has full support whenever $0 < s < 1$. Results are qualitatively similar under alternative values of these two noise probabilities, provided that they are not set too close to zero.

[8] The parameter grids are as follows: $q \in \{0.02m \mid m = 0, \ldots, 50\}$; $r \in \{0.05m \mid m = 0, \ldots, 20\}$; $s \in \{0.05m \mid m = 0, \ldots, 20\}$; $\lambda \in \{0.0002m \mid m = 1, \ldots, 20\}$ for FSE and PSE; and $\lambda \in \{0.0002m \mid m = 1, \ldots, 50\} \cup \{0.01 + 0.002m \mid m = 1, \ldots, 70\}$ for 2P.

[9] We use a subject-level holdout, with 70% of subjects used for estimation and the remaining 30% reserved for validation. Bootstrap standard errors are computed by resampling subjects. We use 200 bootstrap replications and apply a coordinate-descent algorithm initialized at the estimates from the 70% sample.

Table C7: Maximum-likelihood estimates and model comparison.

Treatment	Model	Estimates (standard errors)				Estimation			Validation
		$\hat{\lambda} \times 100$	$\hat{q}$	$\hat{r}$	$\hat{s}$	LL	AIC	BIC	LL
FSE	Full	0.24	0.18	0.45	0.50	−3222	6452	6472	−1479
		(0.038)	(0.035)	(0.046)	(0.075)				
	$r = 0$	0.30	0.28	0	0.50	−3523	7052	7067	−1616
		(0.037)	(0.005)		(0.074)				
	$s = 0$	0.06	0.10	0.45	0	−3714	7435	7450	−1564
		(0.023)	(0.054)	(0.036)					
	$r = 0$	0.20	0.58	0	0	−4273	8550	8560	−1745
	$s = 0$	(0.024)	(0.044)						
	$q = 0$	0.06	0	0.40	—	−3736	7477	7487	−1584
		(0.018)		(0.034)					
	$q = 0$	0.14	0	0	—	−4632	9266	9271	−1963
	$r = 0$	(0.025)							
PSE	Full	0.28	0.32	0.40	0.35	−1808	3625	3642	−851
		(0.047)	(0.041)	(0.070)	(0.070)				
	$r = 0$	0.36	0.42	0	0.35	−1942	3890	3903	−903
		(0.039)	(0.045)		(0.069)				
	$s = 0$	0.06	0.08	0.35	0	−1987	3980	3993	−927
		(0.020)	(0.073)	(0.043)					
	$r = 0$	0.24	0.70	0	0	−2264	4532	4541	−1030
	$s = 0$	(0.045)	(0.035)						
	$q = 0$	0.06	0	0.35	—	−1994	3993	4001	−930
		(0.013)		(0.043)					
	$q = 0$	0.08	0	0	—	−2427	4856	4861	−1082
	$r = 0$	(0.011)							
2P	Full	0.80	0.18	0.65	0.15	−1261	2531	2548	−463
		(0.122)	(0.071)	(0.078)	(0.094)				
	$r = 0$	13.60	0.10	0	0.10	−1640	3286	3299	−678
		(0.728)	(0.033)		(0.039)				
	$s = 0$	0.48	0.06	0.60	0	−1307	2620	2633	−471
		(0.094)	(0.040)	(0.070)					
	$r = 0$	1.20	0.02	0	0	−1893	3791	3800	−791
	$s = 0$	(0.564)	(0.018)						
	$q = 0$	0.34	0	0.60	—	−1330	2665	2673	−485
		(0.092)		(0.058)					
	$q = 0$	1.00	0	0	—	−1963	3929	3933	−816
	$r = 0$	(0.092)							

Notes: Bootstrap standard errors are reported in parentheses. For the precision parameter λ, estimates and standard errors are multiplied by 100 for readability. LL denotes log-likelihood. AIC and BIC denote the Akaike information criterion and the Bayesian information criterion, respectively. Validation LL is calculated using the 30% subject-level holdout sample. An em dash indicates a parameter that is not identified under the imposed restriction.

Bayes' rule, the posterior probability that subject i is of the overbidding type is given by

$$p_i = \frac{q \prod_{t \in T_i} \gamma(v_{it}, b_{it})}{(1-q) \prod_{t \in T_i} \sigma(v_{it}, b_{it}) + q \prod_{t \in T_i} \gamma(v_{it}, b_{it})}. \tag{C2}$$

Each subject is classified as the overbidding type if $p_i \geq 0.9$ and as the baseline type if $p_i \leq 0.1$; subjects with intermediate probabilities are left unclassified.[10] Table C8 cross-tabulates the resulting type classifications with the clustering results from Section C.4. Figure C8 at the end of this subsection illustrates observed and simulated bids for the baseline and overbidding types.

Table C8: Posterior type classification.

Cluster	FSE			PSE			2P		
	Base.	Uncl.	Over.	Base.	Uncl.	Over.	Base.	Uncl.	Over.
1	48	6	5	30	1	2	62	1	2
	(81%)	(10%)	(8%)	(91%)	(3%)	(6%)	(95%)	(2%)	(3%)
2	46	0	5	14	1	5	6	0	1
	(90%)	(0%)	(10%)	(70%)	(5%)	(25%)	(86%)	(0%)	(14%)
3	22	2	0	11	0	0	2	0	0
	(92%)	(8%)	(0%)	(100%)	(0%)	(0%)	(100%)	(0%)	(0%)
4	5	0	0	1	0	1	0	0	1
	(100%)	(0%)	(0%)	(50%)	(0%)	(50%)	(0%)	(0%)	(100%)
5	2	0	19	1	2	13	0	1	5
	(10%)	(0%)	(90%)	(6%)	(13%)	(81%)	(0%)	(17%)	(83%)
Total	123	8	29	57	4	21	70	2	9
	(77%)	(5%)	(18%)	(69%)	(5%)	(26%)	(86%)	(3%)	(11%)

Notes: Subjects are classified into types according to the posterior probability (C2) of being the overbidding type: Base. (baseline), $p_i \leq 0.1$; Uncl. (unclassified), $0.1 < p_i < 0.9$; Over. (overbidding), $p_i \geq 0.9$. Clusters are shown in Figures C3–C5. Each cell reports the number of subjects, with percentages in parentheses indicating shares within each cluster; in the Total row, percentages indicate shares within each treatment.

Finally, we examine how the presence of the overbidding type affects the entry behavior of baseline-type bidders. Figure C7 plots, for each treatment, observed entry rates by value for baseline-type subjects together with the corresponding QRE predictions. For the QRE predictions, we show both the full model and a counterfactual. We compute the counterfactual QRE σ by setting the share of the overbidding type to zero ($q = 0$) while holding the baseline-type parameters at their full-model estimates. This counterfactual therefore removes the overbidding type from the opponent population.

[10] Using a more stringent classification rule yields similar results. Specifically, when subjects are classified as the overbidding type if $p_i \geq 0.95$ and as the baseline type if $p_i \leq 0.05$, the number of unclassified subjects increases by five in FSE and by one in 2P, while remaining unchanged in PSE.

As the figure shows, in both FSE and PSE, the full-model QRE predicts lower entry than the counterfactual over a wide range of values, with the difference particularly pronounced at low values. In PSE, the counterfactual predicts high entry even at low values, whereas the full model predicts substantially lower entry for such values. This is because, in the absence of the overbidding type, the PSE lottery generates substantial interim expected profits from entry for bidders at all values. Overall, in both treatments, the full model better captures the observed entry patterns than does the counterfactual. By contrast, in 2P, the full-model and counterfactual predictions are nearly identical, and both are consistent with the observed entry behavior.

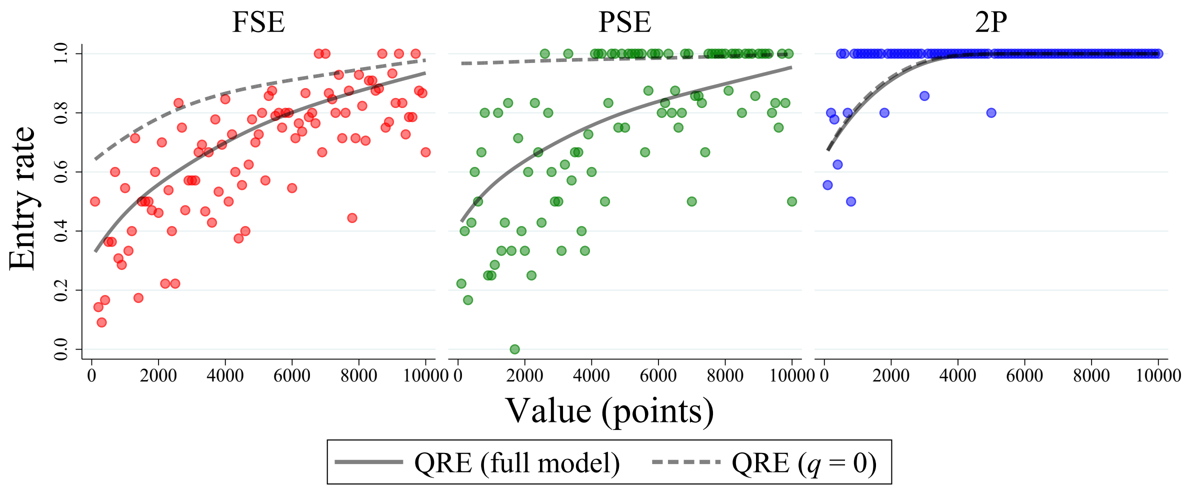


Figure C7: Observed and predicted entry rates for the baseline type by value.

Notes: Circles indicate observed entry rates for subjects classified as the baseline type. The solid curves show the QRE predictions implied by the baseline-type strategy σ under the full model. The dashed curves show the counterfactual QRE predictions when $q = 0$, with the baseline-type parameters λ and r fixed at their full-model estimates.

Table C9 reports aggregate entry rates for the baseline type in each treatment. The results are consistent with Figure C7. In FSE and PSE, the full-model QRE predicts lower entry than the counterfactual and is closer to the observed entry rates. These results suggest that the presence of the overbidding type reduces the entry incentives of baseline-type bidders. In 2P, where value bidding is dominant on the entire bid space, predicted entry remains high regardless of whether the overbidding type is present.

Table C9: Aggregate entry rates for the baseline type.

Treatment	Observed	QRE (full model)	QRE ($q = 0$)
FSE	0.666	0.722	0.868
PSE	0.733	0.769	0.982
2P	0.973	0.954	0.957

Notes: This table uses data from rounds 11–20 in which the opponent is unpaid. Observed rates are calculated for subjects classified as the baseline type. For both QRE columns, predicted entry probabilities are averaged over the same realized values. In the $q = 0$ counterfactual, the baseline-type parameters λ and r are fixed at their full-model estimates.

Computation of the QRE fixed point

For each parameter configuration (λ, q, r, s), we compute the QRE fixed point for the baseline type using discrete-time logit dynamics (Fudenberg and Levine 1998). Let $h \in (0, 1)$ denote the time step. For the slab component, the updating rule is

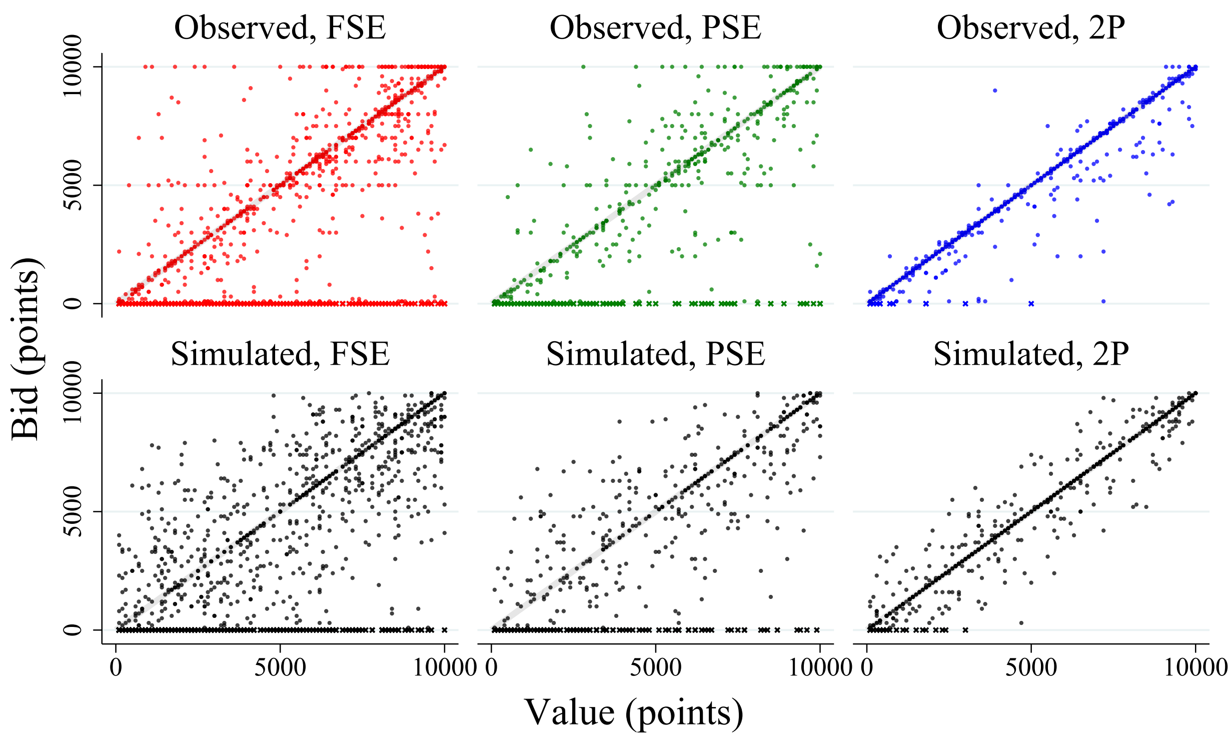
$$\frac{\sigma_{\mathrm{SL}}^{t+h}(v,b) - \sigma_{\mathrm{SL}}^{t}(v,b)}{h} = \frac{\exp\left[\lambda U^{(1-q)\sigma^t + q\gamma}(v,b)\right]}{\sum_{b' \in B} \exp\left[\lambda U^{(1-q)\sigma^t + q\gamma}(v,b')\right]} - \sigma_{\mathrm{SL}}^{t}(v,b),$$

where $t \in \{0, h, 2h, \ldots\}$ and

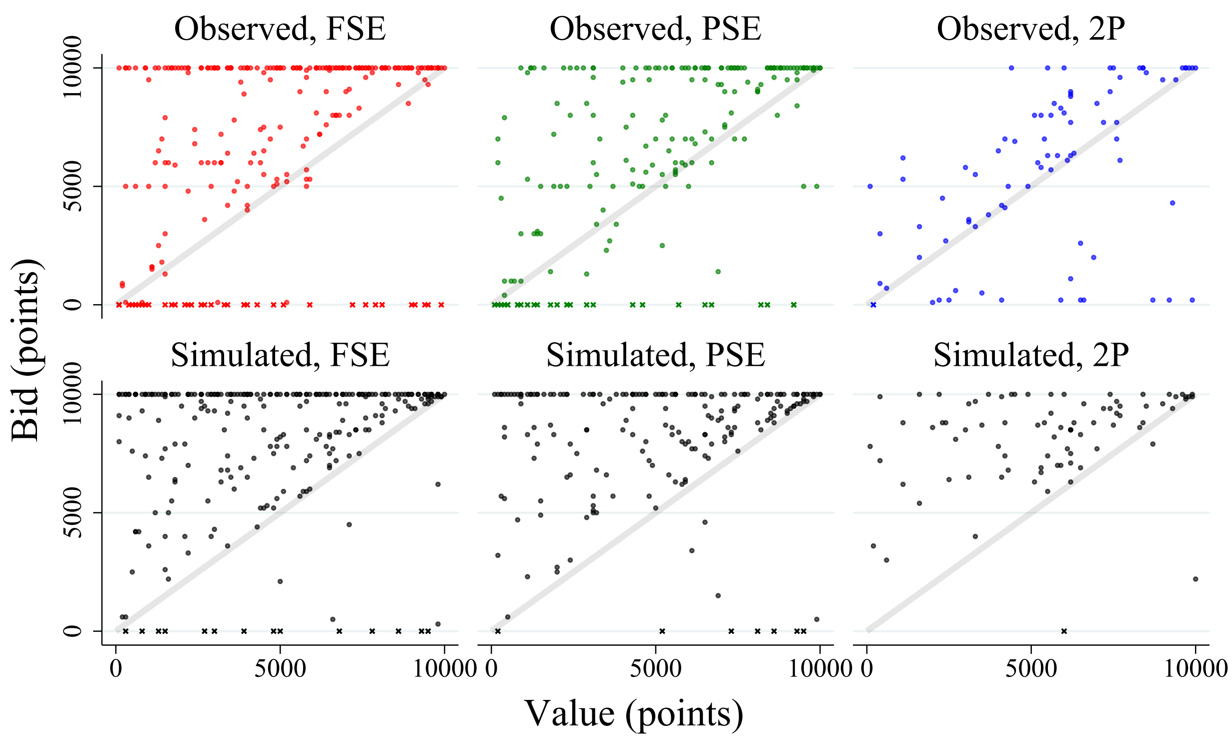
$$\sigma^t = r\sigma_{\mathrm{SP}}^t + (1-r)\sigma_{\mathrm{SL}}^t.$$

The spike component σ_{SP}^t is updated simultaneously using the analogous logit rule with the choice set restricted to $\{0, v\}$. The overbidding-type strategy γ is fixed for a given value of s. The time step is set to $h = 0.3$. Convergence is declared when the maximum absolute change across all elements of both components falls below 10^{-8}.

For the first parameter configuration in the grid search, the initial strategies are uniform (on $\{0, v\}$ for σ_{SP}^0 and on B for σ_{SL}^0). For each subsequent configuration, the QRE obtained for the preceding parameter configuration is used as the initial strategy. As a check for multiplicity, we also used several alternative initial strategies at the estimated parameters for each treatment and obtained fixed points that were numerically close to the QRE obtained using our baseline initialization procedure.



(a) Baseline type

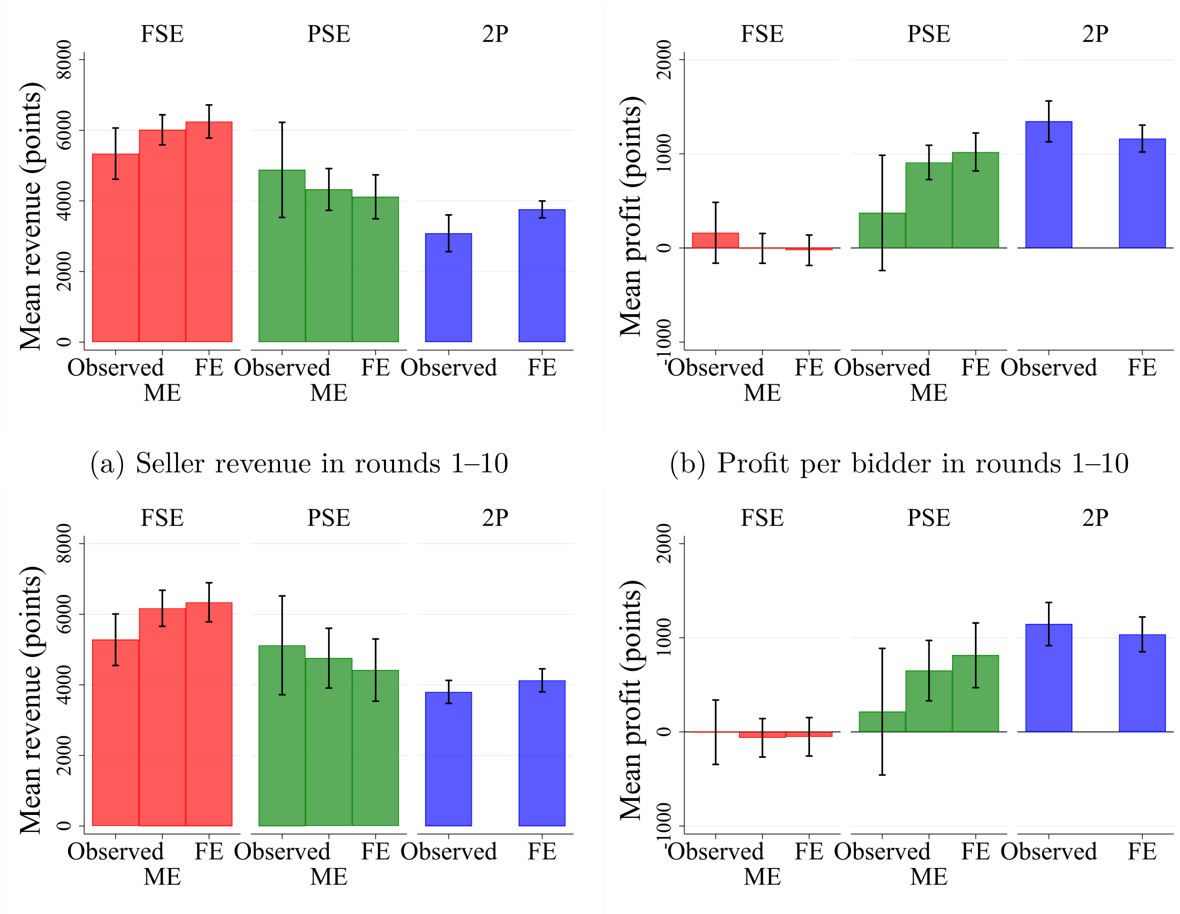


(b) Overbidding type

Figure C8: Observed and simulated bids by type.

Notes: Observed bids are based on data from rounds 11–20 in which the opponent is unpaid. Simulated bids are drawn from the estimated behavioral strategies σ and γ using the values realized in the experiment. The solid diagonal line represents value bidding.

C.6 Supplementary figures and tables



(a) Seller revenue in rounds 1–10

(b) Profit per bidder in rounds 1–10

(c) Seller revenue in rounds 11–20

(d) Profit per bidder in rounds 11–20

Figure C9: Mean seller revenue and bidder profit in rounds 1–10 and 11–20.

Notes: Bars show means across independent matching groups. Profit is measured per bidder. For each group, the equilibrium benchmarks for revenue and profit are computed using the values realized in that group. Capped spikes indicate 95% confidence intervals.

Table C10: Mixed-effects linear probability models for entry decisions controlling for the bidder's value in the previous round.

Dependent variable	Entry	
	First 10 rounds	Last 10 rounds
(Constant)	0.625^{***}	0.477^{***}
	(0.044)	(0.049)
PSE	0.046	0.218^{*}
	(0.072)	(0.101)
2P	0.279^{***}	0.357^{***}
	(0.051)	(0.081)
Round	-0.008^{*}	-0.003
	(0.003)	(0.002)
PSE × Round	-0.006	-0.004
	(0.005)	(0.005)
2P × Round	0.007	0.006
	(0.004)	(0.003)
Value / 1000	0.050^{***}	0.058^{***}
	(0.004)	(0.004)
PSE × Value / 1000	-0.007	-0.011
	(0.007)	(0.009)
2P × Value / 1000	-0.036^{***}	-0.046^{***}
	(0.006)	(0.005)
Previous value / 1000	-0.002	-0.001
	(0.003)	(0.003)
PSE × Previous value / 1000	0.003	-0.003
	(0.005)	(0.004)
2P × Previous value / 1000	0.000	0.002
	(0.004)	(0.003)
Previous opponent's bid / 1000	-0.007	-0.012^{***}
	(0.003)	(0.003)
PSE × Previous opponent's bid / 1000	-0.003	0.002
	(0.005)	(0.006)
2P × Previous opponent's bid / 1000	0.006	0.015^{***}
	(0.004)	(0.003)
Previous opponent entered	0.006	0.065^{*}
	(0.026)	(0.030)
PSE × Previous opponent entered	0.105	-0.006
	(0.054)	(0.050)
2P × Previous opponent entered	0.000	-0.046
	(0.042)	(0.047)
Observations	2,740	3,082

Notes: The dependent variable is $\mathbf{1}\{b_{it} > 0\}$, where $\mathbf{1}\{\cdot\}$ is the indicator function. FSE is the reference treatment. *Previous value* is $v_{i,t-1}$. All models include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table C11: Mixed-effects probit regression models for entry decisions with lagged payoff measures.

Dependent variable	Entry		
	FSE	PSE	2P
Round	-0.008^{***}	-0.008^{***}	0.000
	(0.001)	(0.001)	(0.001)
Value / 1000	0.050^{***}	0.043^{***}	0.016^{***}
	(0.003)	(0.006)	(0.004)
Previous lottery payoff / 1000	0.006^{*}	0.009^{***}	
	(0.002)	(0.002)	
Previous profit from winning / 1000	0.000	0.000	0.000
	(0.002)	(0.004)	(0.001)
Opponent's payment round	0.067	0.086^{*}	-0.043^{*}
	(0.035)	(0.040)	(0.018)
CRT score	-0.008	-0.016	0.002
	(0.010)	(0.014)	(0.003)
Risk averse	-0.080^{*}	0.044	-0.019
	(0.037)	(0.038)	(0.011)
Observations	3,040	1,558	1,539

Notes: The dependent variable is $\mathbf{1}\{b_{it} > 0\}$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Observations from opponents' payment rounds are included. *Previous lottery payoff* is $l_k(b_{j,t-1})$ if i enters in $t-1$ and zero otherwise, where j is i's opponent in $t-1$. *Previous profit from winning* is $v_{i,t-1} - b_{j,t-1}$ if i wins in $t-1$ and zero otherwise. *Opponent's payment round* is one if t is a payment round for the current opponent and zero otherwise. *Risk averse* is one if i is risk averse in both the gain and loss domains in MPL and zero otherwise. The table reports average marginal effects estimated from mixed-effects probit models. All specifications include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table C12: Mixed-effects linear models for deviations from value bidding among subjects who entered in all rounds.

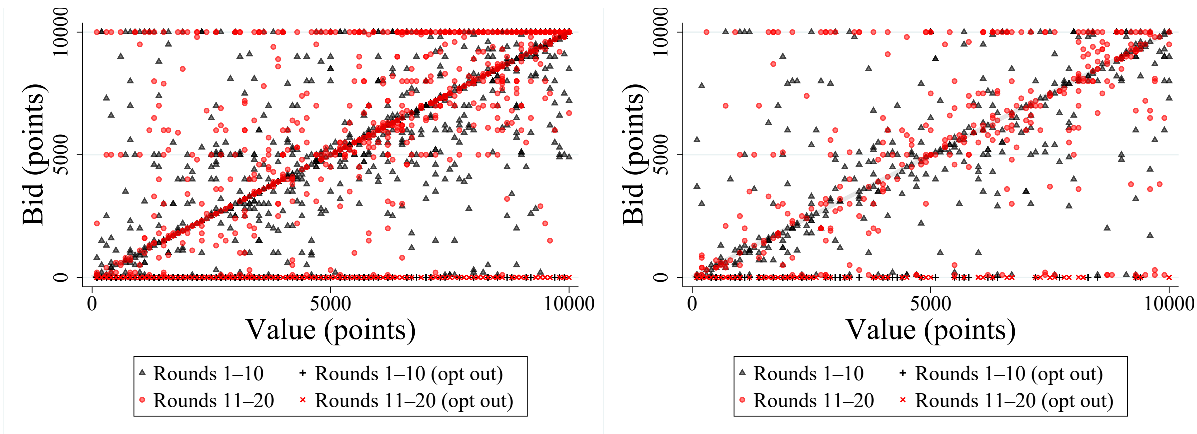
Dependent variable	Deviation	
	First 10 rounds	Last 10 rounds
(Constant)	1998.1^{***}	989.0
	(507.7)	(1045.4)
PSE	47.8	1161.8
	(1475.7)	(1354.9)
2P	-1842.0^{**}	-976.5
	(677.0)	(1092.8)
Round	-46.3	69.2
	(86.6)	(62.0)
PSE × Round	103.8	-2.0
	(152.8)	(77.9)
2P × Round	109.6	-67.0
	(90.4)	(63.0)
Value / 1000	-342.9^{***}	-290.1^{**}
	(69.9)	(85.3)
PSE × Value / 1000	-90.0	-104.4
	(101.0)	(104.4)
2P × Value / 1000	235.2^{**}	259.5^{**}
	(75.9)	(86.4)
Previous opponent's bid / 1000	169.6^{**}	2.0
	(59.1)	(40.9)
PSE × Previous opponent's bid / 1000	-89.7	11.2
	(69.5)	(69.1)
2P × Previous opponent's bid / 1000	-156.5^{*}	-12.2
	(63.1)	(42.7)
Previous opponent entered	-317.1	479.9
	(469.7)	(256.7)
PSE × Previous opponent entered	200.1	-592.0
	(1181.2)	(631.2)
2P × Previous opponent entered	89.2	-197.3
	(578.1)	(301.7)

Notes: The dependent variable is $b_{it} - v_{it}$. The sample is restricted to subjects who entered in all rounds. All specifications include random intercepts for matching groups and subjects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. For the first 10 rounds, linear-combination tests for the effect of the previous opponent's bid yield $p = 0.004$, $p = 0.028$, and $p = 0.549$ for FSE, PSE, and 2P, respectively. The corresponding p-values for the last 10 rounds are $p = 0.961$, $p = 0.813$, and $p = 0.403$.

Table C13: Fixed-effects linear regression models for signed and absolute deviations from value bidding among entrants.

Dependent variable	Deviation			Absolute deviation		
	FSE	PSE	2P	FSE	PSE	2P
	(1)	(2)	(3)	(4)	(5)	(6)
Value / 1000	-333.8^{***}	-372.1^{***}	-106.4^{***}	-96.3^{**}	-152.6^{**}	66.0^{*}
	(34.9)	(42.0)	(14.2)	(29.1)	(41.9)	(21.9)
Previous opponent's bid / 1000	70.2^{***}	83.6^{**}	-6.4	47.2^{**}	30.0	-4.4
	(14.3)	(24.0)	(10.3)	(15.2)	(25.7)	(15.6)
Previous opponent entered	-192.6	-269.9	266.8	-400.2^{**}	-2.8	-78.0
	(132.6)	(250.2)	(233.8)	(118.5)	(145.0)	(229.7)
Opponent's payment round	-487.5	-759.4	-720.9	1121.5^{**}	756.6^{*}	1097.5^{**}
	(345.8)	(443.5)	(454.8)	(330.8)	(250.9)	(347.8)
(Constant)	1879.7^{***}	1769.7^{***}	-424.9	2575.0^{***}	2349.4^{***}	1166.7^{***}
	(272.6)	(280.3)	(393.3)	(208.8)	(249.8)	(244.5)
Observations	2,265	1,264	1,489	2,265	1,264	1,489

Notes: The dependent variables are $b_{it} - v_{it}$ and $|b_{it} - v_{it}|$. The sample is restricted to observations with $b_{it} > 0$. Observations from opponents' payment rounds are included. All specifications include subject and round fixed effects. Cluster-robust standard errors at the group level are reported in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

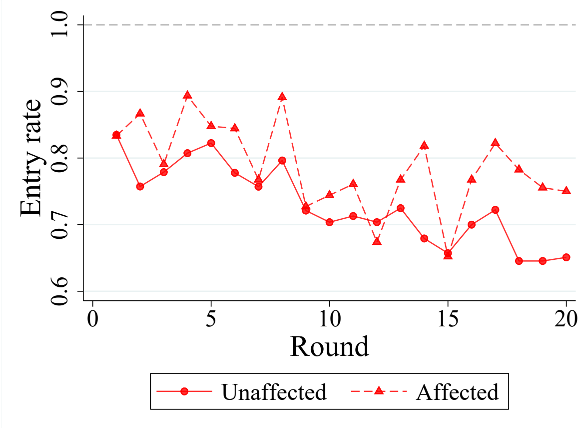


(a) Unaffected

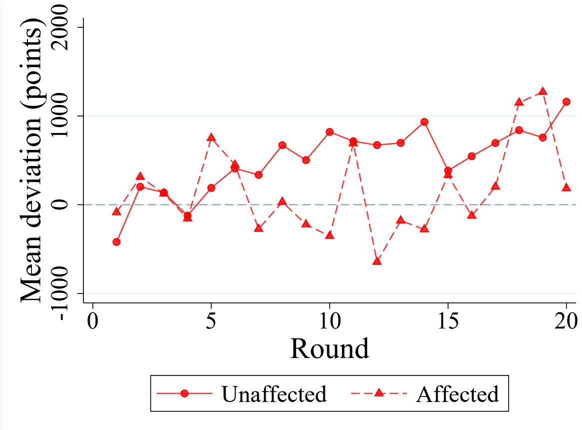
(b) Affected

Figure C10: Bids versus values.

Notes: The left and right panels plot bids from FSE sessions unaffected by and affected by technical issues during the instruction phase, respectively (see footnote 27 of the main paper). The solid diagonal line represents value bidding.



(a) Entry rate



(b) Mean deviation

Figure C11: Entry rates and mean deviations from value bidding by round.

Notes: The solid and dashed lines with markers represent the data from FSE sessions unaffected by and affected by technical issues during the instruction phase, respectively (see footnote 27 of the main paper). The mean deviations in panel (b) are calculated conditional on entry.

Table C14: Regression models controlling for technical issues during the instruction phase.

Dependent variable	Entry	Deviation	Absolute deviation
Round	-0.008^{***}	37.8^{**}	11.4
	(0.001)	(13.5)	(10.7)
Value / 1000	0.051^{***}	-333.0^{***}	-99.6^{**}
	(0.003)	(33.6)	(28.8)
Previous opponent's bid / 1000	-0.011^{***}	74.1^{***}	45.7^{**}
	(0.002)	(15.6)	(15.8)
Previous opponent entered	0.059^{*}	-216.6	-378.5^{**}
	(0.023)	(137.3)	(115.9)
Opponent's payment round	0.069	-500.0	1149.0^{***}
	(0.036)	(347.3)	(324.4)
CRT score	-0.006	37.5	91.3^{*}
	(0.010)	(60.4)	(36.3)
Risk averse	-0.077^{*}		
	(0.037)		
Affected	0.057	-506.2	238.1
	(0.031)	(304.1)	(279.3)
(Constant)		1718.5^{***}	1543.9^{***}
		(345.2)	(282.3)
Observations	3,040	2,267	2,267

Notes: This table corresponds to Tables 3 and 5 in the main paper. The *affected* indicator equals one if the session was affected by technical issues during the instruction phase and zero otherwise. The three models in this table use data from the FSE treatment, since these issues occurred only in this treatment. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

D Lemmas

This subsection provides some technical lemmas for the characterization of the ME equilibrium in FSE. As in the main paper, let $z \in [0,1]^n$ denote an opt-out strategy. For value $v \in V$, define the interim profit from entry with value bidding by

$$\text{(D1)} \quad \begin{aligned} U^z(v) &= E_{v_j}\left[vz(v_j) + (v - \min\{v, v_j\} + l_{\text{FSE}}(v_j))(1 - z(v_j)) \mid v_i = v\right] \\ &= \rho\,(v - l_{\text{FSE}}(v))\,z(v) + (1-\rho)\sum_{w \in V} \frac{1}{n}\,(\min\{v, w\} - l_{\text{FSE}}(w))\,z(w) + \delta_{\text{FSE}}, \end{aligned}$$

where the second equality follows from equation (A3) in the main paper. For the arguments below, we extend $U^z(v)$ algebraically to any $z \in \mathbb{R}^n$.

Lemma D1. *Fix any $v^k \in V$ with $v^k > l_{\text{FSE}}(v^k)$. The following system of n linear equations has a unique solution $z \in \mathbb{R}^n$:*

$$\text{(D2)} \qquad z(v') = 1,$$

$$\text{(D3)} \qquad \rho\,(v - l_{\text{FSE}}(v))\,z(v) + (1-\rho)\sum_{w \in V} \frac{1}{n}\,(\min\{v, w\} - l_{\text{FSE}}(w))\,z(w) = -\delta_{\text{FSE}}$$

for every $v' < v^k$ and $v \geq v^k$, respectively.

Proof of Lemma D1. For notational simplicity, we let $\Delta = 100$ denote the value increment. Subtracting equation (D3) for $v = v^{n-1}$ from that for $v = v^n$ yields

$$z(v^{n-1}) = \frac{\rho(v^n - l_{\text{FSE}}(v^n)) + \Delta(1-\rho)/n}{\rho(v^{n-1} - l_{\text{FSE}}(v^{n-1}))} z(v^n).$$

The characterization of the lottery in Lemma A1 of the main paper implies

$$\rho(l_{\text{FSE}}(v^{n-1}) - l_{\text{FSE}}(v^n)) = \Delta(1-\rho) - \Delta(1-\rho)/n,$$

so that

$$z(v^{n-1}) = \frac{\rho(v^{n-1} - l_{\text{FSE}}(v^{n-1})) + \Delta}{\rho(v^{n-1} - l_{\text{FSE}}(v^{n-1}))} z(v^n).$$

More generally, a similar calculation yields the following for each m with $k \leq m < n$:

$$\text{(D4)} \qquad \begin{aligned} z(v^m) = &\frac{\rho(v^m - l_{\text{FSE}}(v^m)) + (\rho + (1-\rho)(m+1)/n)\Delta}{\rho(v^m - l_{\text{FSE}}(v^m))} z(v^{m+1}) \\ &+ \frac{(1-\rho)\Delta}{\rho(v^m - l_{\text{FSE}}(v^m))} \sum_{h \geq m+2} \frac{z(v^h)}{n}. \end{aligned}$$

The coefficient on $z(v^{m+1})$ is greater than one and those on $z(v^h)$ are positive, because l_{FSE} is decreasing on V and therefore $v^m \geq v^k > l_{\text{FSE}}(v^k) \geq l_{\text{FSE}}(v^m)$.

Proceeding recursively, we can express $z(v^m)$, for every $m \geq k$, as a positive multiple of $z(v^n)$. We then substitute these expressions (together with $z(v) = 1$ for every $v < v^k$) into equation (D3) for $v = v^n$. Since $w > l_{\text{FSE}}(w)$ for every $w \geq v^k$, all terms involving $z(v^n)$ have positive coefficients. Hence, the resulting equation uniquely determines $z(v^n)$. Equation (D4) then uniquely determines $z(v^{n-1}), \ldots, z(v^k)$ recursively. Together with (D2), this yields a unique solution $z \in \mathbb{R}^n$. □

In the following, for any integer k such that $v^k > l_{\text{FSE}}(v^k)$, let $z^k \in \mathbb{R}^n$ denote the unique vector given by Lemma D1. Whenever both z^k and z^{k-1} are defined, we define

$$\zeta^k(v) = z^k(v) - z^{k-1}(v)$$

for each $v \in V$. The following identity will be useful:

$$\begin{aligned} \text{(D5)} \qquad & U^{z^k}(v) - U^{z^{k-1}}(v) \\ & = \rho\,(v - l_{\text{FSE}}(v))\,\zeta^k(v) + (1-\rho) \sum_{w \geq v^{k-1}} \frac{1}{n}\,(\min\{v, w\} - l_{\text{FSE}}(w))\,\zeta^k(w), \end{aligned}$$

for each $v \in V$, where the equality follows from $z^k(w) = z^{k-1}(w) = 1$ for every $w < v^{k-1}$.

Lemma D2. *(i) If $z^k(v) \leq 0$ for some $v \geq v^k$, then*

$$z^k(v^k) \leq z^k(v^{k+1}) \leq \cdots \leq z^k(v^n) \leq 0.$$

(ii) If $z^k(v) > 0$ for some $v \geq v^k$, then

$$z^k(v^k) > z^k(v^{k+1}) > \cdots > z^k(v^n) > 0.$$

Proof of Lemma D2. (i) If $z^k(v) \leq 0$ for some $v \geq v^k$, then equation (D4) implies $z^k(v^n) \leq 0$; otherwise, all $z^k(v^m)$ with $m \geq k$ would be positive. Since the coefficient on $z^k(v^{m+1})$ in equation (D4) is greater than one and all other coefficients are positive, the inequalities in the statement follow recursively.

(ii) The proof is analogous. If $z^k(v) > 0$ for some $v \geq v^k$, equation (D4) implies $z^k(v^n) > 0$. Applying the same equation recursively yields the strict inequalities in the statement. □

Lemma D3. *(i) If $\zeta^{k+1}(v^k) \leq 0$ for some $v^k > l_{\text{FSE}}(v^k)$, then $\zeta^{k+1}(w) \geq 0$ for each $w \geq v^{k+1}$. (ii) If $\zeta^{k+1}(v^k) > 0$ for some $v^k > l_{\text{FSE}}(v^k)$, then $\zeta^{k+1}(w) < 0$ for each $w \geq v^{k+1}$.*

Proof of Lemma D3. Since equation (D4) is linear, ζ^{k+1} satisfies the same recursive relation for every $m \geq k+1$.

(i) To derive a contradiction, suppose that $\zeta^{k+1}(w) < 0$ for some $w \geq v^{k+1}$. The same recursive argument as in Lemma D2 then implies that $\zeta^{k+1}(w) < 0$ for every $w \geq v^{k+1}$. Since $\zeta^{k+1}(v^k) \leq 0$, equations (D3) and (D5) imply

$$0 = U^{z^{k+1}}(v^n) < U^{z^k}(v^n) = 0,$$

a contradiction.

(ii) The result follows by an analogous argument. $\square$

Lemma D4. *Let k be the lowest integer such that $v^k > l_{\mathrm{FSE}}(v^k)$. Then (i) $z^k(v^k) > 0$ and (ii) $U^{z^k}(v^{k-1}) < 0$.*

Proof of Lemma D4. By the minimality of k, $v \leq l_{\mathrm{FSE}}(v)$ for every $v < v^k$.

(i) To derive a contradiction, suppose that $z^k(v^k) \leq 0$. Lemma D2(i) then implies that $z^k(v) \leq 0$ for every $v \geq v^k$. The chosen parameter $\delta_{\mathrm{FSE}} = 1$ satisfies

$$(1-\rho) \sum_{w \leq l_{\mathrm{FSE}}(w)} \frac{1}{n} (w - l_{\mathrm{FSE}}(w)) + \delta_{\mathrm{FSE}} < 0.$$

Since $z^k(v) = 1$ for every $v < v^k$, the second equality in (D1) implies $U^{z^k}(v^n) < 0$. This contradicts $U^{z^k}(v^n) = 0$.

(ii) Since $z^k(v^k) > 0$, Lemma D2(ii) implies that $z^k(v) > 0$ for every $v \geq v^k$. Using $v^{k-1} \leq l_{\mathrm{FSE}}(v^{k-1})$ and $z^k(v^{k-1}) = 1$, the second equality in (D1) implies $U^{z^k}(v^{k-1}) < U^{z^k}(v^k) = 0$. $\square$

Lemma D5. *If $U^{z^k}(v^{k-1}) \leq 0$ for some integer k with $v^k > l_{\mathrm{FSE}}(v^k)$, then $z^k(v^k) > 0$.*

Proof of Lemma D5. If k is the lowest integer such that $v^k > l_{\mathrm{FSE}}(v^k)$, the result follows from Lemma D4(i). Hence, suppose that $v^{k-1} > l_{\mathrm{FSE}}(v^{k-1})$.

To derive a contradiction, suppose that $z^k(v^k) \leq 0$. Lemma D2(i) then implies that $z^k(v) \leq 0$ for every $v \geq v^k$. Since $z^k(v^{k-1}) = 1$ by construction, the second equality in (D1) implies

$$U^{z^k}(v^{k-1}) > U^{z^k}(v^k) = 0.$$

This contradicts $U^{z^k}(v^{k-1}) \leq 0$. $\square$

Lemma D6. *Let k be an integer such that $v^k > l_{\mathrm{FSE}}(v^k)$. The vector $z^k \in \mathbb{R}^n$ is an equilibrium with $z^k(v^k) > 0$ if and only if k is the highest integer among those m that satisfy $v^m > l_{\mathrm{FSE}}(v^m)$ and $U^{z^m}(v^{m-1}) \leq 0$.*

Proof of Lemma D6. First, suppose that k is the highest integer among those m that satisfy $v^m > l_{\mathrm{FSE}}(v^m)$ and $U^{z^m}(v^{m-1}) \leq 0$. Lemma D5 implies that $z^k(v^k) > 0$. We show that z^k is an equilibrium.

First, we show that $z^k(v^k) < 1$. To derive a contradiction, suppose that $z^k(v^k) \geq 1$. This is possible only if $k < n$, because $U^{z^k}(v^n) = 0$. Thus, $\zeta^{k+1}(v^k) = 1 - z^k(v^k) \leq 0$. Lemma D3(i) then implies that $\zeta^{k+1}(w) \geq 0$ for every $w \geq v^{k+1}$. Together with these inequalities, equations (D3) and (D5) imply

$$U^{z^{k+1}}(v^k) = U^{z^{k+1}}(v^k) - U^{z^k}(v^k) \leq U^{z^{k+1}}(v^{k+1}) - U^{z^k}(v^{k+1}) = 0.$$

This contradicts the maximality of k.

Next, z^k is an opt-out strategy because $z^k(v) = 1$ for $v < v^k$ and, by Lemma D2(ii), $z^k(v) \in (0, 1)$ for every $v \geq v^k$. Moreover, no bidder has an incentive to deviate: $U^{z^k}(v) = 0$ for every $v \geq v^k$ by equation (D3), $U^{z^k}(v^{k-1}) \leq 0$, and $U^{z^k}(v) < 0$ for every $v < v^{k-1}$ by the second equality in (D1), using $z^k(v) = z^k(v^{k-1}) = 1$. Hence, z^k is an equilibrium.

Conversely, suppose that z^k is an equilibrium with $z^k(v^k) > 0$. By construction, $z^k(v^{k-1}) = 1$, so $U^{z^k}(v^{k-1}) \leq 0$ in equilibrium. Let m be the highest integer that satisfies $v^m > l_{\text{FSE}}(v^m)$ and $U^{z^m}(v^{m-1}) \leq 0$. Since k itself satisfies these conditions, $k \leq m$.

We show that $k = m$. To derive a contradiction, suppose that $k < m$. Lemma A5 of the main paper implies that $z^k(v) < 1$ for every $v \geq v^k$. Repeated application of Lemma D3(ii) then implies $z^{m-1}(v^{m-1}) < 1$. Hence,

$$\zeta^m(v^{m-1}) = 1 - z^{m-1}(v^{m-1}) > 0,$$

and Lemma D3(ii) implies that $\zeta^m(w) < 0$ for every $w \geq v^m$. Together with these inequalities, equations (D3) and (D5) imply

$$U^{z^m}(v^{m-1}) = U^{z^m}(v^{m-1}) - U^{z^{m-1}}(v^{m-1}) > U^{z^m}(v^m) - U^{z^{m-1}}(v^m) = 0,$$

which contradicts $U^{z^m}(v^{m-1}) \leq 0$. Thus, $k = m$. □

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