Participation, selection and indicative bidding in auctions with costly entry*

Changxia Ke† Greg Kubitz‡ Yang Liu§

November 21, 2025

Abstract

We test the performance of indicative bidding in auctions with costly entry where potential bidders have incomplete information about their private, affiliated values of the asset prior to entry. We analyze indicative bidding's effectiveness in encouraging participation in these auctions and in selecting the participants with the highest valuations to enter the bidding stage. We find that when the entry cost is high, indicative bidding generates significantly more revenue than two benchmark entry mechanisms (i.e., one without entry restrictions and the other imposing a cap on the number of entrants) due to its ability to encourage participation. However, when the entry cost is low, the predicted revenue advantage of indicative bidding is dampened by less efficient selection than that predicted by theory.

JEL Classification: D44, C92, D82.

Keywords: Two-stage auction; Indicative bidding, Costly entry; Experiment

*We are grateful to audiences at the annual Australia New Zealand Workshop on Experimental Economics (ANZWEE), the Asia-Pacific Industrial Organization Conference, the Conference on Contests: Theory and Evidence, and the University of Adelaide for helpful comments and suggestions. All errors remain ours.

†Changxia Ke: School of Economics and Finance, Queensland University of Technology, QLD 4000, Australia. E-mail: changxia.ke@qut.edu.au

‡Greg Kubitz: School of Economics and Finance, Queensland University of Technology, QLD 4000, Australia. E-mail:kubitz@qut.edu.au

§Yang Liu: School of Economics, Finance and Marketing, RMIT University, VIC 3000, Australia. E-mail: laura.liu@rmit.edu.au

1 Introduction

Developing bids for complex assets requires bidders to engage in costly due diligence to assess the value of the target asset. Examples include buyers hiring professional teams to evaluate the target firm in company takeovers, contractors investing in market research to understand procurement requirements in government auctions, and bidders performing detailed site inspections in the sales of natural resource permits. Sellers of these assets indirectly bear this cost through less participation and, consequently, lower winning bids. Limiting the number of bidders who may enter the auction can increase potential bidders' willingness to participate, as they anticipate less competition in the auction. However, when the number of bidders exceeds this limit, a selection mechanism is required. A process that selects bidders with higher expected values for the asset will increase both seller revenue and social welfare.

Indicative bidding is a common practice in real-world auctions, where bidders are shortlisted based on their stated level of interest. These indications typically take the form of non-binding bids or bid ranges.[1] Although the indicative bids do not place restrictions on the final bids, indicative bidding can facilitate efficient selection. When placing an indicative bid, a potential bidder faces the trade-off between choosing a higher bid, which gives a higher chance of being selected, and choosing a lower bid, which reduces the expected level of competition conditional on selection. Bidders with a higher expected value for the asset would prefer entering more often while those with a lower expected value prefer to enter only when competition is low. Despite its common use and theoretical benefits, there is a lack of controlled evidence showing how restricting entry and using indicative bidding as a selection mechanism impacts auction outcomes.[2]

In this paper, we experimentally test the performance of indicative bidding in auctions

[1] See examples in Hansen (2001), Boone and Mulherin (2007) and Gentry and Stroup (2019), as well as discussions in Kagel et al. (2008) and Quint and Hendricks (2018). A example local to the researchers unfolded in 2020 when Deloitte oversaw a takeover auction for Virgin Australia. According to Khadem (2020), out of 20 initial potential bidders, at least 8 indicative bids were lodged, but only 4 were shortlisted. The importance of the size of the shortlist was highlighted by 'Brookfield who reportedly pulled out because it did not want to be part of a group of more than two bidders within a short timeframe.'

[2] The only evidence that the authors are aware of is provided by Kagel et al. (2008) who compare indicative bidding to an entry rights auction. The comparisons to the current paper are discussed as part of the related literature.

with costly entry, focusing on its effectiveness in encouraging participation and addressing selection inefficiency. For this purpose, we compare an indicative bidding mechanism to two other entry mechanisms. The first, which we denote as the unrestricted entry mechanism (*Unr*), does not restrict the number of bidders in the auction and therefore does not have a selection process. The second, which we denote as the restricted entry mechanism (*Res*), imposes an entry cap. When the number of interested bidders exceeds the cap, the mechanism randomly selects bidders from this pool to participate in the auction. In addition to implementing an entry cap, the indicative bidding mechanism (*Ind*) allows bidders to indicate two levels of interest, with selection priority given to those that indicate a high level of interest.

Our theoretical predictions and experimental design utilize the model of indicative bidding introduced by Quint and Hendricks (2018). In this model, there is a set of risk-neutral potential bidders, each with a private value for a single, indivisible asset. Potential bidders do not know this value initially; instead, they each receive a private signal. A bidder learns the value only after entering the auction and paying a fixed entry cost that is identical for every entrant. The auction proceeds as a second-price sealed-bid auction with no reservation value.[3] In our experiment, each potential bidder's private valuation of the asset is the sum of their initial private signal and a common value component that is learned after entering the auction.[4] Each bidder's initial private signal is independently drawn and uniformly distributed.[5]

We develop a theoretical framework for the experimental setting to generate predictions about the relative performance of a class of entry mechanisms that contains the three mechanisms implemented in the experiment. We define the *participation effect* and the *selection effect* of an entry mechanism as the two components of the expected revenue loss

[3] While the first-price auction is commonly used in these settings, the second-price auction guarantees the existence and uniqueness of a symmetric equilibrium for our theoretical framework of the experimental settings. Both auction formats provide similar quantitative predictions for revenue and surplus for parameters used in our experiment, see Quint and Hendricks (2018), Tables 1 and 3.

[4] The common value assumption represents a special case of highly correlated information acquired after entry. We adopt this because it both mirrors the information structure of our leading examples (Li and Zheng, 2009; Aradillas-López et al., 2013) and is a setting in which efficient selection is particularly critical for auction revenue.

[5] For each participant, we randomly draw an integer between 1 and 100. The details of the experimental implementation are given in Section 3, and the experimental instructions are given in Appendix C.

relative to the expected second-highest value among potential bidders. The *participation effect* is the revenue loss from potential bidders choosing not to enter the auction, and the *selection effect* is the loss from the mechanism failing to select the highest-valued bidders for the auction stage.

We first use these definitions to highlight the revenue trade-off caused by changing the maximum number of bidders allowed into the auction. When this maximum number is lowered, potential bidders are more willing to opt in given the promise of less competition, reducing the revenue loss attributable to the *participation effect*. However, the highest valued bidders are less likely to be selected, increasing the revenue loss attributable to the *selection effect*. Secondly, we show that the relative change of these two effects depends on the level of entry costs. When entry costs are sufficiently high, the reduction in *participation effect* dominates and restricting entry increases revenue, implying that *Res* outperforms *Unr*. On the other hand, when entry costs are sufficiently low, the increase in *selection effect* dominates and restricting entry decreases revenue. Lastly, we show that allowing bidders to indicate two levels of interest always reduces the *participation effect*. Moreover, for the value distributions and number of bidders considered in the experiment, it also reduces the *selection effect*. Therefore, *Ind* generates at least as much revenue as *Res* for any entry cost and generates more than *Unr* for sufficiently high entry cost.

To test these theoretical predictions, we compare the three mechanisms in a 2×3 experiment both when the entry cost is relatively low (*low-cost* condition) and relatively high (*high-cost* condition). We observe in the experiment that both *Ind* and *Unr* generate higher average revenues than *Res* under the *low-cost* condition. In the *high-cost* condition the average revenue from *Ind* is higher than both *Res* and *Unr*. Therefore, as predicted by theory, *Ind* indeed generates a weakly higher average revenue than *Res* and *Unr* in both cost conditions.

Despite the overall alignment of the revenue ranking with the theoretical predictions, we also observe three general deviations from the theoretical predictions. First, deviations from equilibrium entry strategies led to a significantly higher *selection effect* for *Res* and *Ind* under both cost conditions. We identify this as the reason why *Ind* does not outperform *Unr* in the *low-cost* condition. Second, potential bidders in *Ind* had a higher participation

rate, and therefore a lower *participation effect* than predicted, which helps to explain why *Ind* outperforms *Res* in the *high-cost* condition. Lastly, in all treatments, bidders bid on average above their value in the second-price auction. This is consistent with previous experimental findings in second-price auctions and does not significantly impact cross-treatment revenue comparisons.

Finally, we compare the bidders' profits and social welfare, which includes both auction revenue and bidders' profits, generated by the three mechanisms. We find that *Ind* generates significantly more social welfare than *Unr* under both cost conditions and *Res* generates more welfare than *Unr* under the low-cost condition. Restricting entry reduces the total cost of entry and accounts for the predicted and realized gains in welfare in both *Res* and *Ind*. Although *Ind* generates more revenue than *Res*, it does not produce significantly greater social welfare because the extra revenue comes at the expense of bidders' profits; it comes primarily from increased participation rather than improved selection. Overall, *Res* generates at least as much profit for the bidders as the other two mechanisms under both cost conditions.

1.1 Related Literature

This paper contributes to understanding how selling mechanisms impact the seller's revenue and social welfare when bidding is costly and therefore entry is endogenous. In this setting, Milgrom (2004) describes why auction outcomes may suffer from the presence of too many potential bidders: "Buyers are naturally reluctant to begin an expensive, time-consuming evaluation of an asset when they believe they are unlikely to win at a favorable price." When bidders are ex-ante symmetric, e.g., when they learn their values after entering, the decision to participate becomes an increasingly difficult coordination problem as the number of potential bidders grow. Reducing the number of potential bidders can reduce this coordination problem and increase revenue and social welfare (Levin and Smith, 1994; Li and Zheng, 2009). Similarly, when bidders have information about their value prior to the choice of entry, their cutoff value for entry decreases in the number of potential bidders (Samuelson, 1985; Li and Zheng, 2009) which can reduce revenue and welfare.

In this case, entry fees or reserve prices can increase the seller's revenue by screening out potential bidders with low signals about their value (Menezes and Monteiro, 2000; Lu, 2009). Likewise, when bidder's have private entry costs, entry fees can be used to screen out bidders with high entry costs and improve revenue (Moreno and Wooders, 2011; Li and Zheng, 2009; Lu, 2010).

Unlike the mechanisms described above, two-stage auctions include a pre-qualification stage where each bidder's probability of entry depends on the choices of the other potential bidders.[6] The first stage can coordinate entry of bidders while endogenously screening them according to their private characteristics. A simple version of this pre-qualification is a fixed, commonly known cap on the number of bidders allowed to enter the auction. When bidders have no information prior to entry, Moreno and Wooders (2011) shows that an entry cap can improve social welfare and, when combined with an entry fee, increase seller revenue. Using the Quint and Hendricks (2018) framework with a single positive entry message, we show that imposing an entry cap can increase seller revenue when potential bidders have information about their value before entry and entry costs are sufficiently high. This improvement does not rely on the use of entry fees. Our experimental results show that while social welfare is improved, the increase in seller's revenue from the entry cap does not materialize due to selection inefficiencies stemming from entry decisions that differ from equilibrium predictions.

In addition to capping the number of bidders that are allowed to enter the auction, indicative bidding lets potential bidders indicate their level of interest in the asset. While Ye (2007) shows that there are no fully separating symmetric equilibria when bids are non-binding, Quint and Hendricks (2018) shows that a symmetric semi-separating equilibrium exists and can improve selection relative to a simple entry cap. Our experimental results support the hypothesis that two levels of indicative bidding can improve seller's revenue. However, this effect was driven mainly by the increase in participation (reduction of the *participation effect*) rather than improved selection.

As an alternative to indicative bidding, the entry rights auction has potential bidders

[6] Two-stage auctions that impose restrictions on second stage bids without restricting the number of bidders can also help aggregate bidder information (Fujishima et al., 1999; Perry et al., 2000).

participate in a first-stage auction to qualify for the main auction.[7] In contrast to indicative bidding, Ye (2007) shows that efficient entry can be induced by an entry rights auction in a symmetric equilibrium. Moreover, Lu et al. (2021) identify that the revenue maximizing two-stage auction involves message-dependent shortlisting and payment rules so that the number of entrants and their first-stage payments are endogenously determined.[8] However, Kagel et al. (2008) provided experimental evidence that indicative bidding preformed as well as the entry rights auction in selecting bidders with the highest value while also achieving higher revenue and fewer bidder bankruptcies. In contrast to our study, they did not compare the observed selection efficiency of indicative bidding to a theoretical benchmark, as no equilibrium prediction was available. We instead draw on the equilibrium prediction from Quint and Hendricks (2018) to design the indicative bidding stage with a restricted set of messages, enabling direct comparison between experimental outcomes and theoretical predictions. Our findings are nonetheless conceptually consistent: selection efficiency is lower than predicted when entry is restricted, yet indicative bidding still performs relatively well.

Relatedly, the "qualifying auction" studied by Boone and Goeree (2009)—in which a non-binding first stage is used to exclude the bidder with the lowest bid—was experimentally tested by Boone et al. (2009). They observe arbitrarily high bidding (a babbling equilibrium) in the non-binding stage, along with lower auction revenue compared to a standard English auction. Crucially, their model assumes costless entry, so bidding higher in the indicative stage does not increase expected costs. In our setting, entry is costly, and a higher indicative bid increases expected entry costs.[9]

Finally, fully sequential auctions have been studied by Bulow and Klemperer (2009) and Roberts and Sweeting (2013), where in the later, bidders have private information

[7] Bhattacharya et al. (2014) shows that entry rights auctions can outperform first price auctions without entry restrictions whenever pre-entry signals are imprecise, a la Levin and Smith (1994), or very informative, a la Samuelson (1985).

[8] Lu and Ye (2013) show that when bidders have private entry costs, the socially efficient and revenue optimal two-stage auction can be implemented using a first-stage all-pay auction with reserve price.

[9] There are only a handful of additional experiments on auctions with endogenous entry. The majority of these papers focus on testing revenue equivalence (Ivanova-Stenzel and Salmon, 2008) and winner's curse (Cox et al., 2001; Palfrey and Pevnitskaya, 2008) in standard auctions with free entry following the extensive literature on auctions with fixed or exogenous number of bidders summarized in Kagel and Levin (1990) and Kagel and Levin (2011).

about their value prior to entry. This mechanism allows the seller to approach and solicit bids from potential bidders sequentially. Each potential bidder's entry decision depends on the current bid and therefore bidders may want to place a jump bid to discourage future entry. While aggressive early bids have a direct effect of increasing auction revenue, by deterring future entry expected revenue may actually decrease.[10] Lu et al. (2021) show that the revenue maximizing multi-stage shortlisting rule involves sequentially engaging the potential bidders with the highest pre-entry value. However, like the entry-rights auction, this mechanism requires an upfront, non-refundable payment before bidders can conduct due diligence.

The remainder of the paper is organized as follows. Section 2 provides the theoretical framework for our experimental design, and Section 3 presents the details of the design and experimental hypotheses. The results are given in Section 4 and Section 5 concludes.

2 Theoretical Framework

We adopt the environment and assumptions about the two-stage mechanisms used by Quint and Hendricks (2018). There is a set of $N \geq 3$ risk neutral potential bidders, each with private value V_i for a single indivisible asset. Potential bidders do not know V_i initially, instead having a private signal S_i. The value can be fully learned after entering the auction and paying an entry cost c. This cost is assumed to be identical between bidders and can reflect the cost of participation or due diligence.

For this paper, we assume that the value of each potential bidder is the sum of the initial signal (S_i) and a common value component of the asset, denoted T, which is only learned by bidders who enter the auction stage. The value of the asset for each potential bidder is therefore $V_i = S_i + T$. We further assume that bidders' signals are uniformly distributed on $[0, \bar{S}]$ and $\{S_1, \ldots, S_N, T\}$ are mutually independent. The environment is then determined by the number of potential bidders N, the symmetric entry cost c, and the distributions of the private signals and the common component. We assume that $c \in (0, \bar{S} + \mathbb{E}[T])$ which

[10] Sweeting and Bhattacharya (2015) find that when entry is selective, i.e., bidders with higher expected value are more likely to enter, both the sequential bidding and entry-rights auctions outperform unrestricted entry in efficiency and expected revenue for a range of parameters.

rules out the uninteresting cases where everyone opts in or everyone opts out regardless of their signal. The equilibrium relevant components of the of the environment can be summarized by $\mathcal{X} = (\bar{S}, \mathbb{E}[T], N, c)$.

In this setting, we consider two-stage mechanisms that consist of a communication stage and an auction stage. In the communication stage, potential bidders privately know S_i and can send one message from a finite set indexed by nonnegative integers, $m \in \{0, 1, \ldots, \overline{M}\}$.[11] Potential bidders can choose message $m = 0$ if they wish to opt out or they can participate by sending a positive message. Given the messages sent, potential bidders are selected into the auction stage via a precommitted selection process that caps the number of bidders at $n \geq 2$. Potential bidders who send the highest positive messages are selected sequentially until all n positions are filled, with the ties broken randomly. The auction stage is a standard second-price auction with no reservation price. A two-stage mechanism can be summarized by the maximum number of bidders allowed (n) and the number of positive messages available $(\overline{M})$.

Given an environment $\mathcal{X}$, there is an essentially unique symmetric equilibrium for any two-stage mechanism $\mathcal{M} = (n, \overline{M})$.[12] This equilibrium is partially separating in the communication stage: potential bidders with higher signals send weakly higher messages. Strategies in this stage can be summarized by cutoff signals α_m for which potential bidders are indifferent between sending message m and $m + 1$. In equilibrium, sending m is optimal for all bidders with $S_i \in [\alpha_m, \alpha_{m+1}]$.

2.1 Revenue loss, *participation* and *selection effects*

For a given environment, we assess the performance of a mechanism in the face of entry costs by comparing its expected revenue, denoted $\Pi(\mathcal{M}, \mathcal{X})$, to the expected revenue in the same environment without entry costs. When there is no entry cost, each bidder will always opt in, there is no benefit from restricting entry, and the auction revenue is equal

[11] While this set can be countably infinite in principle, in any symmetric equilibrium only a finite number of messages are ever used (see Quint and Hendricks (2018), Lemma 1).

[12] Formal details of the assumptions required for the existence of a symmetric equilibrium are given in Assumptions 1 and 2 in Quint and Hendricks (2018). In our setting, the existence and essential uniqueness follows from three conditions: the mutual independence of $\{S - 1, \ldots, S_N, T\}$, the uniform distribution of each S_i, and the fact that T is a common value.

to the value of bidder with the second-highest valuation. We denote the revenue in the environment without entry costs as $\Pi(\mathcal{X}_0)$ where $\mathcal{X}_0$ is identical to $\mathcal{X}$ except where $c = 0$. Hence, for environment $\mathcal{X}$ we define the total revenue loss from costly entry when using mechanism $\mathcal{M}$ as $RL(\mathcal{M}, \mathcal{X}) \equiv \Pi(\mathcal{X}_0) - \Pi(\mathcal{M}, \mathcal{X})$.

To define and separate the *participation* and *selection effects*, we consider the revenue of the counterfactual scenario where all potential bidders who send positive entry messages enter the auction stage, regardless of the mechanism's restriction on the number of bidders and the selection process. We denote this hypothetical revenue as $\hat{\Pi}(\alpha_0(\mathcal{M}), \mathcal{X})$.[13] Then, for a given mechanism and environment, we define the *participation* and *selection effects*, respectively, as $PE(\mathcal{M}, \mathcal{X}) \equiv \Pi(\mathcal{X}_0) - \hat{\Pi}(\alpha_0(\mathcal{M}), \mathcal{X})$ and $SE(\mathcal{M}, \mathcal{X}) \equiv \hat{\Pi}(\alpha_0(\mathcal{M}), \mathcal{X}) - \Pi(\mathcal{M}, \mathcal{X})$. The *participation effect* quantifies the expected revenue loss attributable to potential bidders who opt out while the *selection effect* quantifies the expected revenue loss attributable to mechanism's failure to advance the highest-valued participating bidders to the auction stage. It follows that the total revenue loss is the sum of the *participation* and *selection effects*.

In the following subsections, we first examine how revenue is affected by restricting entry when bidders can send only two messages—"opt in" or "opt out." We then consider the impact of allowing for additional indicative messages in the communication stage.

2.1.1 Entry restriction

Consider a two-stage mechanism where potential bidders can only opt in or opt out of the auction ($\overline{M} = 1$). The symmetric equilibrium is then characterized by a single cutoff signal (α_0) in the communication stage. For a given environment and restriction on the number of bidders, this cutoff signal satisfies:

$$p_0(\alpha_0 + \mathbb{E}[T] - c) - c \sum_{k=1}^{N-1} p_k \min\left\{1, \frac{n}{k+1}\right\} = 0, \tag{1}$$

[13] We use the notation $\alpha_0(\mathcal{M})$ to represent the equilibrium cutoff signal of bidders that are indifferent between opting out with $m = 0$ or participating with $m = 1$ given mechanism $\mathcal{M}$. This cutoff signal is sufficient to characterize the *participation effect* and *selection effects* for a given $\mathcal{X}$.

where $p_k = \binom{N-1}{k}\left(\frac{\bar{S}-\alpha_0}{\bar{S}}\right)^k\left(\frac{\alpha_0}{\bar{S}}\right)^{N-1-k}$ is the probability that k other potential bidders choose $m = 1$. Equation 1 implies that a potential bidder with the cutoff signal is indifferent between opting in and opting out of the auction. This bidder would only win the auction when no other potential bidders opt in, which happens with probability p_0. The bidder's expected profit in this case is $\alpha_0 + \mathbb{E}[T] - c$. When $k \geq 1$ other potential bidders opt in, the potential bidder with the cutoff signal is selected with probability $\min\left\{1, \frac{n}{k+1}\right\}$; if selected, the bidder pays the entry cost but does not win the auction.

With an two-stage mechanism that restricts entry ($n < N$), a potential bidder that opts in is less likely to be selected and pay the entry cost whenever more than n potential bidders opt in. Lemma 1 shows that α_0 decreases as n decreases, implying that more restrictive entry attracts potential bidders with lower initial signals.

Lemma 1. *For a given environment and set of mechanisms with $\overline{M} = 1$, a mechanism with a lower maximum number of bidders (n) allowed has a lower cutoff signal (α_0).*

While entry restrictions encourage more potential bidders to opt in, if the number of interested bidders exceeds the restriction, some who opt in will not be selected for the auction stage. Thus, as the cap on the number of bidders becomes more restrictive, decreases in the *participation effect* may be offset by increases in the *selection effect*. Proposition 1 formalizes the countervailing nature of the two effects on revenue from restricting entry.

Proposition 1. *For a given environment and a set of mechanisms with $\overline{M} = 1$, a mechanism with a lower maximum number of bidders (n) decreases the participation effect and increases the selection effect.*

The impact of restricting entry on auction revenue depends on the relative magnitude of these countervailing effects. With a low entry cost, most potential bidders are willing to opt in even when entry is unrestricted. In this case, restricting entry has a small impact in reducing the *participation effect* but significantly amplifies the *selection effect*, resulting in lower expected revenue. However, when the entry cost is high, fewer potential bidders choose to opt in. In this case, restricting entry substantially reduces the *participation effect* while causing only a modest increase in the *selection effect*, resulting in lower expected

revenue loss. Proposition 2 shows that when the cost of entry is high enough it is revenue maximizing to restrict the number of bidders to $n = 2$. On the other hand, when the entry cost is sufficiently low, placing no restriction on the number of bidders will maximize revenue.

Proposition 2. *Fix an environment other than entry cost and consider a set of mechanisms with* $\overline{M} = 1$.

(*a*) *For a sufficiently low entry cost, a mechanism which restricts the number of bidders* ($n < N$) *leads to more expected revenue loss than the unrestricted mechanism with* $n = N$.

(*b*) *For a sufficiently high entry cost, a mechanism that restricts the number of bidders to* $n = 2$ *leads to less expected revenue loss than mechanisms that allow* $n > 2$ *bidders.*

2.1.2 Indicative bidding

We now consider the impact of adding an additional message ($\overline{M} = 2$) to the communication stage of the mechanism. With two messages, there are up to two cutoff signals in the symmetric equilibrium, α_0 and α_1. The condition for the signal of the potential bidder who is indifferent between opting in and opting out is

$$p_{0,0}(\alpha_0 + \mathbb{E}[T] - c) - c\sum_{j=0}^{N-1}\sum_{k=1}^{N-1-j} p_{k,j} \min\left\{1, \frac{n-j}{k+1}\right\} = 0, \tag{2}$$

where $p_{k,j} = \binom{N-1}{j}\binom{N-1-j}{k}\left(\frac{\bar{S}-\alpha_1}{\bar{S}}\right)^j\left(\frac{\alpha_1-\alpha_0}{\bar{S}}\right)^k\left(\frac{\alpha_0}{\bar{S}}\right)^{N-1-j-k}$ is the probability that k other potential bidders choose $m = 1$ and j others choose $m = 2$.

Potential bidders will prefer to send a higher entry message exactly when they want to increase their chances of entering the auction despite knowing they face competition. The cutoff signal that is indifferent between choosing $m = 1$ and $m = 2$ must satisfy

$$\sum_{k=n}^{N-1} p_{k,0}\left(1 - \frac{n}{k+1}\right)\left(\frac{\alpha_1 - \alpha_0}{n} - c\right) - c\sum_{j=1}^{N-1}\sum_{k=\max\{0,n-j\}}^{N-1-j} p_{k,j}\left(\min\left\{1, \frac{n}{j+1}\right\} - \frac{\max\{0, n-j\}}{k+1}\right) = 0. \tag{3}$$

The first term is the expected benefit of increasing the probability of entering when no other potential bidders have a signal above α_1, and the second term is the expected cost of increasing the chance of entering the auction when at least one potential bidder has a signal above α_1. In an equilibrium where $m = 2$ is used with positive probability, the cutoff signals must jointly satisfy (2) and (3). When the entry cost is high enough, these equations do not have a solution for $\alpha_1, \alpha_0 \in [0, \bar{S}]$.[14] For higher entry costs, a potential bidder needs a larger expected gain to prefer $m = 1$ over $m = 0$. This raises the cutoff α_0 satisfying (2) for a given α_1. The higher α_0 reduces the expected benefit from choosing $m = 2$ instead of $m = 1$ for a given α_1, and higher entry costs increases the expected cost of entering more often. To keep (3) satisfied, α_1 must also rise. For sufficiently high entry cost (2) and (3) can only be satisfied by $\alpha_1 > \bar{S}$; hence in equilibrium potential bidders choose only $m = 0$ and $m = 1$.

To understand the revenue impacts of adding a second message, we consider the change in *participation* and *selection effects* for a fixed environment. The *participation effect* is only impacted by the change in the cutoff signal α_0. Relative to (1), for fixed α_0 and $\alpha_1 < \bar{S}$, the first term of the left-hand side of (2) is the same and the second term is less negative; a potential bidder sending $m = 1$ is less likely to be selected to enter the auction when facing competition. This increases the expected value of choosing $m = 1$ relative to $m = 0$ and reduces α_0. The following proposition shows that the *participation effect* will be strictly lower when the second entry message is used in equilibrium.

Proposition 3. *For any environment and entry restriction the cutoff value α_0 and the participation effect are weakly lower when $\overline{M} = 2$ than when $\overline{M} = 1$. These reductions are strict when $\alpha_1 < \bar{S}$.*

The availability of a second message will increase the chance that a high-valued bidder with $S_i \in (\alpha_1, \bar{S})$ is selected to enter the auction when $\alpha_1 < \bar{S}$. However, in this case, the second message will also lower α_0, increasing that chance that a low-valued bidder with S_i between α_0 for $\bar{M} = 2$ and α_0 for $\bar{M} = 1$ is selected to enter. Although this suggests that the *selection effect* may not always reduce when a second message is added, for the parameters used in our experimental setting, it does decrease; see Figure 1. For these parameters, the

[14] In this case, the first term of (3) will be less than the second term for all α_1, α_0 that satisfy (2).

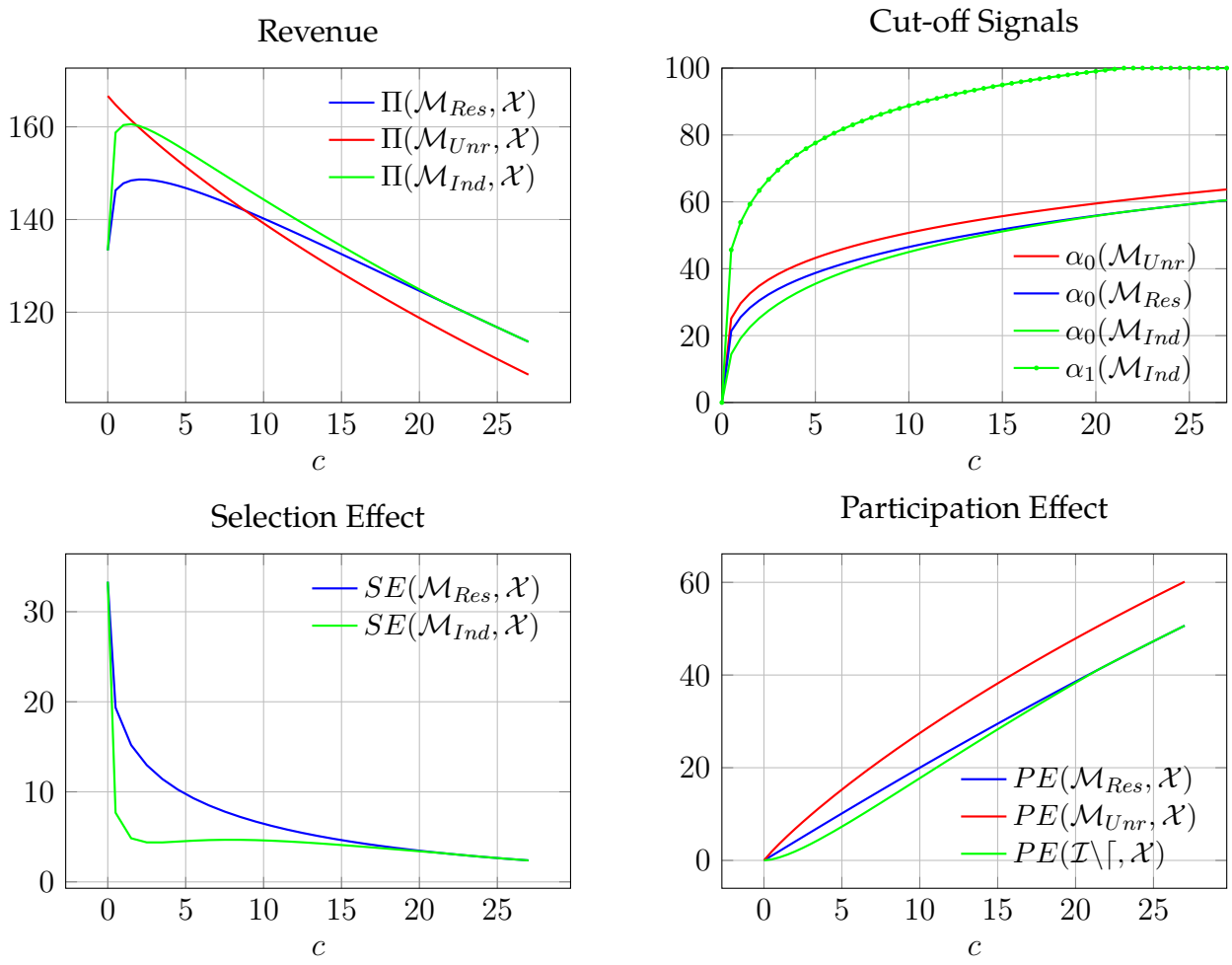


Figure 1: Comparison of revenue, equilibrium cutoff signals, *selection effect* and *participation effect* for the three two-stage mechanisms $\mathcal{M}_{Unr} = (5, 1)$, $\mathcal{M}_{Res} = (2, 1)$ and $\mathcal{M}_{Ind} = (2, 2)$ under the environment $\mathcal{X} = (100, 100, 5, c)$ and plotted against different values of c which include our *low-cost* $c = 5$ and *high-cost* $c = 25$ conditions.

second message reduces both the *participation effect* and the *selection effect* and therefore leads to additional revenue for all entry costs. However, for sufficiently small cost, the *selection effect* with two messages will be larger than the *participation effect* when there is no restriction on entry. Therefore, similar to the result of Proposition 1, *Unr* is the the revenue maximizing mechanism for sufficiently small entry costs.

3 Experimental design and hypotheses

Based on the theoretical predictions given in Section 2, we design a 2×3 experiment to test the performance of unrestricted entry ($\mathcal{M}_{Unr}$), restricted entry ($\mathcal{M}_{Res}$), and indicative bidding ($\mathcal{M}_{Ind}$) mechanisms in both low entry cost ($c = 5$) and high entry cost ($c = 25$) environments. For each treatment, we fix the environment (other than the entry cost) so that $N = 5$, $\bar{S} = 100$ and $\mathbb{E}[T] = 100$. As described in Section 2, two-stage mechanisms can be summarized by the number of bidders allowed to enter, n, and the number of positive messages available, $\overline{M}$: $\mathcal{M} = (n, \overline{M})$. The mechanisms tested are $\mathcal{M}_{Unr} = (5, 1), \mathcal{M}_{Res} = (2, 1)$, and $\mathcal{M}_{Ind} = (2, 2)$.

In the experiment, each two-stage game unfolds in the following way. The computer first independently draws the initial signal S_i for each participant by randomly drawing an integer according to a uniform distribution on [0,100]. Having observed their private signal, the participants choose an entry message. Given the chosen messages, the entrants are selected according to the treatment-specific mechanism. The selected participants are advanced to the auction stage, pay the entry cost c and learn the additional common value T which follows a discrete distribution with probability 1/2 taking the value of 100 and probability 1/4 taking the value of either 0 or 200 respectively.[15] After learning the additional value, a second-price sealed bid auction is conducted. The entrants must place their bid without knowing the number of other entrants they are bidding against. When there is only one entrant, that entrant always wins and pays zero. Once the auction is

[15] The common value T is determined for all participants (within the same group) by randomly drawing two cards each with two possible values, 100 and 0. The computer will randomly assign one of the two values (100 and 0 with equal chance) to each card independently. The sum of the two numbers assigned to the two cards determines the common value. Hence, the common value has 25% being 0, 50% being 100 and 25% being 200. See Appendix C for details on how this was implemented in the experiment.

completed, all participants receive complete feedback on each participant's initial signal, entry decision, bid (if selected to enter), and payoff.[16]

We adopt a hybrid between-subject and within-subject design. In an experimental session, we implement one mechanism per treatment while varying the entry cost within a treatment. Each participant completes 20 rounds of the two-stage game under the same mechanism, with no carryover value between rounds. Participants are randomly assigned to groups of five in round 1 and stay with each other for the first 10 rounds, are randomly rematched again in round 11 (when the cost condition changes), and stay in the same group for the second 10 rounds. The entry cost is set at $c = 5$ (*low-cost*) in rounds 1-10 and at $c = 25$ (*high-cost*) in rounds 11-20. After 20 rounds, the computer then randomly draws one round to determine the payment.[17]

The experiment was programmed on oTree (Chen et al., 2016) and was run in November 2019. We recruited 360 participants across campus at Zhejiang Gongshang University (China) and conducted four sessions for each of the three treatments, with 30 participants in each session.[18] The sessions lasted approximately 1.5 hours and the average payment was 75 RMB, including a show-up fee of 30 RMB.

3.1 Predictions and Hypotheses

Table 1 presents the predicted cutoff for each entry message, the total revenue loss (compared with the free entry benchmark) due to costly entry, along with the predicted *selection* and *participation effect*s, auction revenue, bidders' profit, and social welfare under each entry mechanism.

[16] To help participants make their decision, a history table that includes the number of participants who chose to enter, as well as the winner's valuation, bid, and profit in all previous rounds, is displayed on every decision screen after round 1.

[17] To cover the entry cost, participants are given 30 experimental currency (i.e., EC) each round as their initial endowment. Hence, the final payment also includes the (remaining) endowment in the payment round selected. Their earnings from the payment round are converted to RMB using an exchange rate of 1 EC = 1.5 RMB.

[18] To help the participants understand the experimental procedure, at the beginning of each session, a video that summarizes the experimental instructions was played after they read the printed instructions. Participants were also given control questions which they had to answer fully correctly before entering the main part of the experiment. Please see Appendix C for the experimental instructions and relevant screenshots.

Table 1: Theoretical Predictions

	Low-cost (c=5)			High-cost(c=25)		
	Unr	**Res**	**Ind**	**Unr**	**Res**	**Ind**
α_0	43.23	38.74	35.50	62.62	59.28	59.28
α_1			77.59			-
Revenue Loss (RL)	15.27	19.87	10.89	56.77	49.93	49.93
participation effect	15.27	10.12	9.77	56.77	47.28	47.28
selection effect	0	9.75	1.12	0	2.65	2.65
Social welfare	167.10	167.74	172.02	121.96	131.00	131.00
Auction revenue	151.39	146.79	154.86	109.89	116.73	116.73
Bidders' profit	15.71	20.95	17.16	12.07	14.27	14.27

As indicated by Proposition 2 (and shown in Table 1), *Unr* generates more revenue than *Res* when the entry cost is low; and when entry cost is high, the reverse order holds. Moreover, from Figure 1, *Ind* will lead to weakly higher revenues than *Res* for either cost condition. This leads to the following revenue rankings:

Hypothesis 1 (**Revenue ranking**). *When the entry cost is low,* $\Pi(\mathcal{M}_{Ind}, \mathcal{X}) > \Pi(\mathcal{M}_{Unr}, \mathcal{X}) > \Pi(\mathcal{M}_{Res}, \mathcal{X})$*; when the entry cost is high,* $\Pi(\mathcal{M}_{Ind}, \mathcal{X}) = \Pi(\mathcal{M}_{Res}, \mathcal{X}) > \Pi(\mathcal{M}_{Unr}, \mathcal{X})$.

Proposition 1 and Proposition 2 characterize the direction and the magnitude of changes in the *participation* and *selection effects* with respect to the entry restriction, n, when there are two entry messages ($\overline{M} = 1$). Proposition 3 further shows that the *participation effect* (weakly) decreases when a second message is added. Figure 1 shows that the *selection effect* also weakly decreases. The comparisons of these effects across the three mechanisms and two cost conditions are summarized by the following hypotheses.

Hypothesis 2 (**Participation effect**). *When the entry cost is low,* $PE(\mathcal{M}_I, \mathcal{X}) < PE(\mathcal{M}_R, \mathcal{X}) < PE(\mathcal{M}_U, \mathcal{X})$*; when the entry cost is high,* $PE(\mathcal{M}_I, \mathcal{X}) = PE(\mathcal{M}_R, \mathcal{X}) < PE(\mathcal{M}_U, \mathcal{X})$.

Hypothesis 3 (**Selection effect**). *When the entry cost is low,* $0 = SE(\mathcal{M}_U, \mathcal{X}) < SE(\mathcal{M}_I, \mathcal{X}) < SE(\mathcal{M}_R, \mathcal{X})$*; when the entry cost is high,* $0 = SE(\mathcal{M}_U, \mathcal{X}) < SE(\mathcal{M}_I, \mathcal{X}) = SE(\mathcal{M}_R, \mathcal{X})$.

By limiting the number of bidders, both the restricted and the indicative bidding mechanisms increase bidders' profit by reducing the number of bidders that pay the entry

cost.[19] This benefit for bidders leads to social welfare improvement. When entry costs are low, higher bidder profits offset the lower revenue from restricting entry, and the unrestricted and restricted mechanisms generate a comparable social welfare. When entry costs are high, restricting entry generates more revenue and more bidders' profits, leading to greater social welfare. In addition, when both messages are used, the indicative bidding mechanism can also generate higher social welfare by selecting bidders with higher expected values into the auction. Therefore, we have the following hypothesis on the ranking of social welfare among the three mechanisms.

Hypothesis 4 (**Social Welfare**). *When the entry cost is low, $\mathcal{M}_{Ind}$ generates more social welfare than $\mathcal{M}_{Res}$ and $\mathcal{M}_{Unr}$; when the entry cost is high, both $\mathcal{M}_{Ind}$ and $\mathcal{M}_{Res}$ generate more social welfare than $\mathcal{M}_{Unr}$.*

4 Experimental Results

In this section, we report our main experimental results. In Section 4.1, we compare auction revenues between treatments and examine how revenue rankings are affected by the *participation* and *selection effects*. Section 4.2 reports individual bidding and entry choices and analyzes how they impact the *participation effect*, the *selection effect*, and the observed revenue ranking. We compare social welfare and bidder's profit across treatments in Section 4.3.

4.1 Auction revenue: *participation* and *selection effects*

Table 2 presents the results from panel regressions of auction revenue under each cost condition, estimated with group-level random effects. In all regressions, the *Unr* treatment is set as the baseline group. In Model 1, *Res* and *Ind* treatments are compared with the *Unr* treatment respectively, while in Model 2, the second highest value of each group is also added to control for differences in the values drawn for each treatment.[20] The estimates

[19] See Equations (10) and (11) in Appendix A.

[20] Participants valuations are randomly drawn by the computer program in each session in the experiment. Controlling for the second highest value in each group reduces variations in revenue from these draws.

do not differ qualitatively between the two models, and hence we will only focus on the second model. When the entry cost is low, the revenue generated in the *Res* treatment is around 13.91 units lower than that of the *Unr* treatment ($p < 0.01$), and 10.59 units lower than that of the *Ind* treatment ($p < 0.01$). Although revenue is also slightly lower in the *Ind* treatment than in the *Unr* treatment, the difference is not statistically significant ($p = 0.53$). Under the *high-cost* condition, the average revenue in the *Ind* treatment is 25.37 units higher than in the *Unr* treatment ($p < 0.01$), and is also around 20 units higher than in the *Res* treatment ($p = 0.03$). Although the *Res* treatment is predicted to yield higher revenue than *Unr* under the *high-cost* condition, our data provide no evidence of this advantage: average revenue is only 5.65 units higher, a difference that is not statistically significant ($p = 0.54$). These results offer partial validation for Hypothesis 1.

Table 2: Panel regressions on auction revenue

	Model 1		**Model 2**	
	Low cost	High cost	Low cost	High cost
Unr (Cons.)	156.3***	107.1***	-1.926	-30.25***
	(5.726)	(7.455)	(5.927)	(9.195)
Res	-15.51*	-2.121	-13.91***	5.653
	(8.098)	(10.54)	(5.205)	(9.272)
Ind	-7.217	24.79**	-3.313	25.37***
	(8.098)	(10.54)	(5.206)	(9.265)
V_2			0.939***	0.840***
			(0.0276)	(0.0394)
# of Obs.	720	720	720	720
# of Groups	72	72	72	72

Note: Both Model 1 and Model 2 use panel regressions, while model 2 further controls for the second-highest value in the group (V_2). *** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

Result 1. *When the entry cost is low, Ind and Unr generate similar revenue and they both generate significantly higher revenue than Res; when the entry cost is high, the revenue generated by Ind treatment is significantly higher than Res and Unr.*

Having established the overall revenue ranking of the mechanisms, we next examine how entry choices (*participation effect*) and the selection process (*selection effect*) separately impact the revenue of each mechanism.[21] For each treatment, we compare the average of

[21] These effects are formally defined in Section 2.1.

the observed effects and the predicted effects given the private values drawn by bidders.[22] These are presented in Table 3. While the predicted effects are calculated using the equilibrium entry strategies, the observed effects instead use the actual entry messages chosen by the participants. To isolate these effects from the impact of potential over-/underbidding behavior we replace actual bids with equilibrium bids for both the predicted and observed effects. A summary table used to calculate these effects can be found in Table B-3 and Table B-4 in Appendix B.

Table 3: *Participation effect* and *Selection effect*

	participation effect				***selection effect***			
	Low cost		**High cost**		**Low cost**		**High cost**	
	Obs	**Pred**	**Obs**	**Pred**	**Obs**	**Pred**	**Obs**	**Pred**
Unr	18.54	14.57	62.2	61.78	0	0	0	0
	(47.40)	(45.04)	(86.54)	(83.89)	(0)	(0)	(0)	(0)
Res	14.93*	10.82	48.63	47.45	16.18***	10.28	6.99***	2.04
	(46.77)	(44.08)	(73.15)	(74.93)	(14.15)	(9.87)	(12.20)	(4.33)
Ind	10.65	9.50	33.07***	53.89	12.68***	4.83	7.55***	2.15
	(38.01)	(39.85)	(67.91)	(82.40)	(14.15)	(6.24)	(12.67)	(4.60)

Note: Columns labeled "**Obs**" present the observed *participation effect* and *selection effect*, assuming participants follow equilibrium bids. Columns "**Pred**" present the predicted effects, using the actual values drawn in the experiment and assuming participants all follow the equilibrium entry and bidding behaviors. Numbers in the round parentheses are the standard deviations. Asterisks next to the observed effects stand for the significance level of the t-test (clustered on the group level) comparing the observed effects to the equilibrium predictions. *** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

As shown in Table 3, observed *participation effects* generally exceed predicitions in the low-cost conditions but are similar to or smaller than the predicted effects in high-cost conditions. With two exceptions, these differences are not statistically significant. In the *Ind* treatment under the *high-cost* condition, the observed *participation effect* is much smaller than its prediction (33.07 vs 53.89, $p < 0.01$). In the *Res* treatment under the *low-cost* condition, the observed effect is slightly larger than predicted and the difference is marginally significant (14.9 vs 10.82, $p = 0.07$). The panel regressions given in Table 4 further examine the relative size of the *participation effect* between the three treatments. In line with predictions, *Ind* treatments have smaller *participation effect*s ($p = 0.052$ under the *low-cost*

[22] These predicted effects differ from those in Table 1 which use the theoretical distribution of signals.

Table 4: Panel regressions: *participation effect* and *selection effect*

	Participation effect				*Selection effect*			
	Model 1		Model 2		Model 1		Model 2	
	Low cost	High cost	Low cost	High cost	Low cost	High cost	Low cost	High cost
Unr (Cons.)	18.54***	62.20***	16.94***	34.09***	-0	-0	-3.821**	-2.195*
	(2.864)	(6.638)	(4.702)	(9.009)	(1.645)	(0.947)	(1.878)	(1.230)
Res	-3.617	-13.57	-3.600	-11.98	16.18***	6.999***	16.22***	7.124***
	(4.050)	(9.388)	(4.041)	(9.458)	(2.326)	(1.340)	(2.298)	(1.333)
Ind	-7.892*	-29.13***	-7.852*	-29.01***	12.68***	7.546***	12.77***	7.555***
	(4.050)	(9.388)	(4.042)	(9.452)	(2.326)	(1.340)	(2.298)	(1.332)
V_{2nd}			0.010	0.172***			0.023***	0.013***
			(0.022)	(0.037)			(0.006)	(0.005)
# of Obs.	720	720	720	720	720	720	720	720
# of Groups	12	12	12	12	12	12	12	12

Note: Model 1 and Model 2 are both panel regressions at the group level, while Model 2 further controls for the second-highest value in the group (v_{2nd}). Standard errors are in the parentheses. *** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

condition and $p < 0.01$ under the *high-cost* condition) compared with the corresponding *Unr* treatments. Although the difference between *Res* and *Unr* is not significant, the sign of the coefficient follows the prediction.[23]

Result 2. *The observed participation effects are mostly aligned with predictions, except that it is significantly smaller than predicted in the Ind treatment under the high-cost condition, and is marginally higher than predicted in the Res treatment under the low-cost condition. Consequently, the participation effect, as predicted, is significantly (weakly) lower in the Ind treatment compared to the Unr treatment under the high-cost (low-cost) condition; in contrast, there is no statistical difference in the observed participation effect between the Res and the Unr treatments, although the estimated differences are in the same direction as the theoretical predictions.*

Turning to the *selection effect*, note first that in the *Unr* treatments no selection occurs, so both the predicted and observed *selection effects* are zero. However, as shown in the right panel of Table 3, the observed *selection effect* in both *Res* and *Ind* is significantly larger than predicted, indicating that inefficient selection reduces revenues in both treatments more than predicted by theory. When the entry cost is high, the message "2" is predicted to be

[23] Similarly, the differences in the *participation effect* between the *Ind* and the *Res* treatments is not statistically significant ($p = 0.29$) under the *low-cost* condition and is marginally lower in *Ind* than *Res* ($p = 0.07$) in the high-cost condition. These two p-values are obtained from the Wald tests (based on the panel regression results in Model 2), comparing the estimates for *Res* and *Ind*.

not useful for separating bidders with high signals from those with low signals, and hence the *Res* and *Ind* treatments are predicted to have the same level of selection inefficiency. This is supported by the results in the *high-cost* condition (7.12 versus 7.56, $p = 0.75$ based on Model 2 in Table 4). However, in the *low-cost* condition, the additional message offered in the *Ind* treatment should be used by participants who received very high signals resulting better selection efficiency and a smaller *selection effect*. Although the observed *selection effect* is indeed smaller in the *Ind* treatment than in the *Res* treatment under the *low-cost* condition, the difference is not statistically significant (12.77 versus 16.22, $p = 0.133$ based on Model 2 in Table 4).[24]

Result 3. *In the Ind and Res treatments, the size of the selection effect is always larger than what is predicted by the theory. Selection inefficiency impacts Ind and Res treatments similarly under both the low-cost and high-cost conditions.*

Combining the results of the revenue ranking and the *participation* and *selection effects*, we find that in the *high-cost* condition the revenue in the *Ind* treatment is much higher than the other two treatments. This is largely driven by more bidders participating than expected by theory which leads to a surprisingly small revenue loss through the *participation effect*. In the *low-cost* condition, the advantage of the *Ind* treatment compared to the *Unr* treatment is dampened by the larger than predicted *selection effect*, such that the predicted treatment difference between *Ind* and *Unr* is not observed. The *Res* treatment, which is predicted to preform well in the *high-cost* condition, generates the lowest revenue among the three mechanisms under both cost conditions. This is driven primarily by a larger than expected *selection effect*.

4.2 Individual behavior

Because treatment-level revenue patterns and deviations from predictions reflect individual behavior, we turn to analyzing bidding and entry behavior to account for these results.

[24] We will further investigate what entry messages individuals chose in Section 4.2.2.

4.2.1 Bidding Behavior

Theory predicts that in a second-price auction, the participants' bids should equal their value for the asset. Figure 2 shows the bids (on the vertical axis) against the bidders' values (on the horizontal axis). Most bids are along or near the 45-degree line. Among the bids that deviate from this line, there appears to be more overbidding than underbidding in all treatments, a phenomenon that has been previously identified in the experimental literature (e.g. Kagel and Levin (2016)). Within each treatment, Figure 2 shows that both over- and underbids fall when moving from low to high cost, with a larger drop in underbids. Because high-cost rounds follow low-cost rounds this pattern suggests that overbidding remains relatively persistent in second-price auctions.

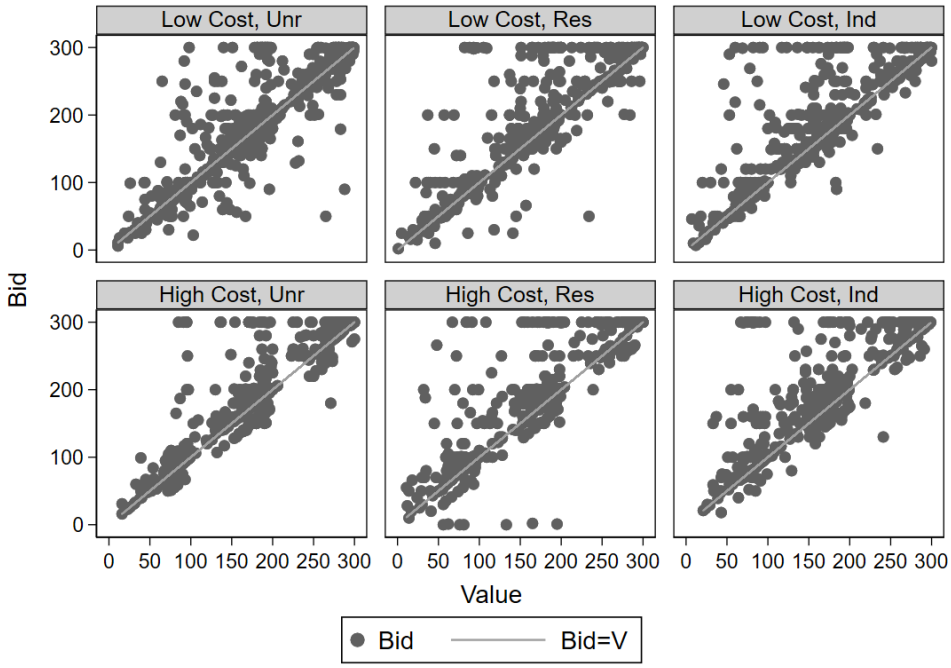


Figure 2: Bidding behavior

We calculate the bid-value ratio (*B-V ratio*), which is the observed bid divided by the valuation v, for each bid. A *B-V ratio* greater (less) than one indicates over- (under-) bidding. To compare bidding behavior across treatments, we regress *B-V ratio* on the treatment dummy for the *low-cost* and *high-cost* conditions separately using a multilevel mixed-effect model. Table 5 presents the regression results. When the entry cost is low, partic-

ipants bid 15%, 22% and 35% more than their valuation in *Unr*, *Res*, and *Ind* treatments, respectively ($p = 0.044$, $p < 0.01$ and $p < 0.01$), while these numbers become 17%, 29% and 29% under the *high-cost* condition. When comparing the overbidding across treatments for a given cost condition, only the difference between *Ind* and *Unr* under low-cost condition is marginally significant at 10% ($p = 0.084$), the remaining comparisons are not statistically significant at conventional levels.[25] Similar levels of overbidding suggests that the revenue ranking across treatments are not driven by differences in bidding strategies. To test this, we re-estimate the panel regressions from Table 2 using counterfactual revenues calculated from observed entry choices and equilibrium bidding strategies (see Table B-5 in Appendix B). The cross-treatment estimates and their significance are unchanged, indicating that overbidding does not drive the treatment differences.

Table 5: Mixed-effect regressions on *bid-value ratio*

	Low cost		High cost	
	Coef	*Wald* test	Coef	*Wald* test
Unr (Cons.)	1.15***	$p = 0.044$	1.17***	$p < 0.01$
	(0.08)		(0.06)	
Res	0.07	$p < 0.01$	0.12	$p < 0.01$
	(0.11)		(0.09)	
Ind	0.20*	$p < 0.01$	0.12	$p < 0.01$
	(0.11)		(0.09)	
σ^2_{group}	0.08		0.02	
	(0.03)		(0.02)	
$\sigma^2_{individual}$	0		0.07	
	(0)		(0.03)	
# of Obs.	1,581		1,252	
# of Groups	72		72	

Note: Mixed-effect regressions control for both group and individual levels of random effects. The number of observations (# of Obs.) is the number of observed bids conditional on entry. *Wald* test are used to compare the observed *B-V ratio* with 1.*** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

Result 4. *In line with previous experimental evidence on second-price auctions, we find significant and consistent overbidding in all treatments. The average overbidding rates are not significantly different across treatments and do not drive treatment differences in revenues.*

[25] We also conduct regressions controlling for demographic factors including gender, major, and risk preference. None of the control variables is significant and the main results do not change.

4.2.2 Entry behavior

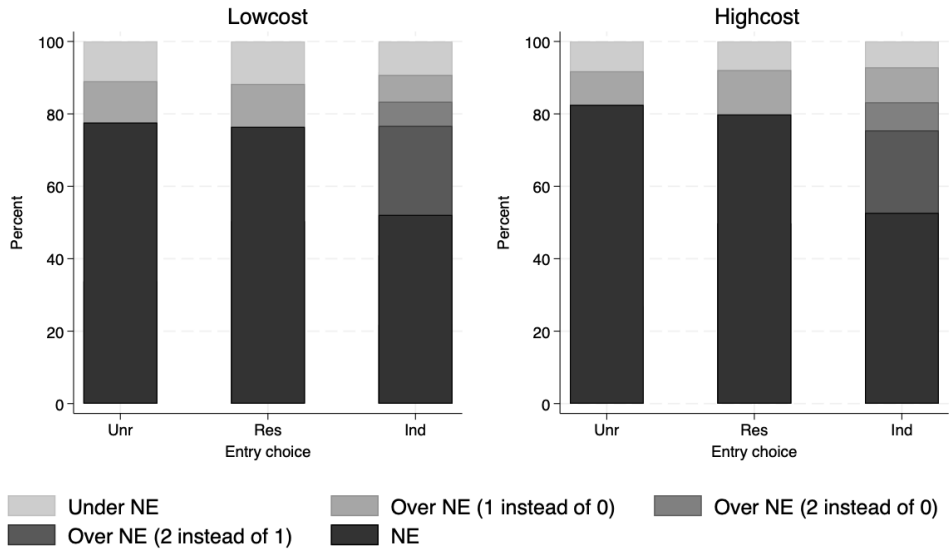
Turning to entry choices, deviations from equilibrium predictions lead to a larger than predicted *selection effect* in the *Res* and *Ind* treatments. We classify participants' entry choices as Nash entry (the chosen matches the equilibrium message of their initial signal), over-entry (the chosen message is higher than the equilibrium message), and under-entry (the chosen message is lower than the equilibrium message). As shown in Figure 3, over- and under-entry patterns are consistent across the cost conditions for each mechanism and are similar between the *Unr* and *Res* treatments. Under the low-cost condition, Nash entry accounts for 78% (*Unr*) and 76% (*Res*) of choices; under the high-cost condition these shares rise slightly to 83% and 80%, respectively. The remaining entry choices are roughly equally divided between over- and under- entry.[26] As a result, the distributions of the number of participants who choose to enter in the *Unr* and *Res* treatments under both cost conditions closely matches equilibrium predictions (see Figure B-1 in Appendix B).

In contrast, just over 50% of the entry choices in the *Ind* treatments match the equilibrium predictions under both cost conditions. The greater complexity of the entry decision plausibly reduces equilibrium-consistent choices; this reduction, in turn, amplifies the *selection effect* relative to the prediction. Moreover, in the *Ind* treatments, there is substantially more over-entry than under-entry in both cost conditions: 39% vs. 9% (*low-cost*) and 40% vs. 7% (*high-cost*). This is mainly driven by the choice of $m = 2$ when $m = 1$ or $m = 0$ is predicted by the equilibrium which make up 32% and 30% of all entry choices under low- and high-cost conditions, respectively.

Because a second-price auction with no reserve yields zero revenue when fewer than two bidders enter, over-entry raises revenue primarily by converting auctions with 1 or 0 entrants into auctions with at least 2 entrants. In *Ind* with high entry cost-where the theory predicts many non-competitive auctions (see B-1 in Appendix B) and over-entry reduces the share of such auctions from 37.09% (predicted) to 19.58% (observed). This shift both attenuates the *participation effect* relative to predictions and pushes revenue above predictions. By contrast, under the *low-cost* condition, the predicted share of non-competitive auctions with 1 or 0 entrants is already small (about 5%), so over-entry can only have a

[26] See the detailed summary statistics in Table B-6 in Appendix B.

Figure 3: Entry choices compared to equilibrium predictions



Note: "Under NE" represents under entry where $M = 0$ is chosen when the equilibrium predicts $M = 1$ or $M = 2$, and where $M = 1$ is chosen when the equilibrium predicts $M = 2$. "Over NE (1 instead of 0)", "Over NE (2 instead of 0)" and "Over NE (2 instead of 1)" denote cases where the observed entry choice M exceeds the equilibrium prediction. i.e., choosing $M = 1$ when the equilibrium predicts $M = 0$, or choosing $M = 2$ when the equilibrium predicts $M = 0$ or $M = 1$. "NE" represents the chosen message matches the equilibrium prediction.

modest impact on reducing the *participation effect* and increasing auction revenue.

To formally compare the entry behavior between treatments, we estimate the probability that each message was chosen given the initial signal s_i in Table 6. Across both cost conditions, participants in *Ind* are significantly more likely to choose to enter (choose $m \in \{1, 2\}$) than those in *Res*, and those in *Res* are more likely to choose to enter than in *Unr* (each $p < 0.01$, t-tests).

Result 5. *About 80% of entry choices in Res and Unr follow equilibrium predictions under both cost conditions, with the remainder evenly split between over- and under-entry. In contrast, only about 50% of the entry choices in Ind are equilibrium consistent, largely due to additional over-entry. This excess entry reduces the participation effect relative to predictions in the high-cost condition, while over- and under-entry choices together raise the selection effect in both Res and Ind under both cost conditions.*

Table 6: Average probability of the entry message being chosen

	Unr			Res			Ind		
	NE	**Mean**	p	**NE**	**Mean**	p	**NE**	**Mean**	p
Low cost									
m=1	0.55	0.55 (0.372)	0.73	0.62	0.64 (0.352)	0.10	0.44	0.22 (0.160)	0.00
m=2							0.20	0.51 (0.376)	0.00
High cost									
m=1	0.35	0.36 (0.352)	0.46	0.38	0.42 (0.369)	0.00	0.40	0.22 (0.157)	0.00
m=2							0	0.29 (0.324)	0.00

Note: The probability of each chosen message given s_i for each observation is estimated by a multilevel ordered logistic model controlled for random effects at the individual and group levels. We leave out the estimation of probability of $m = 0$ chosen, because it can be calculated from $1 - p(enter)$. P values are from *Wald* test clustered at the group level, comparing the observed probability with the corresponding predicted entry threshold. Standard deviations are in parentheses.

4.3 Social welfare

To evaluate the overall impact these mechanisms on both sellers and bidders, we also compare bidders' profit and social welfare (measured as the sum of the bidders' profit and sellers revenue) and across different treatments. The bidders' profit is calculated by summing up the profit of all five potential bidders in each group for each decision round.[27]

The first four columns in Table 7 present the panel regressions of social welfare on a treatment dummy for each cost condition in Model 1, with a control for the highest drawn value V_1 in model 2.[28] For both cost conditions, the social welfare in *Ind* is higher than in *UnR* ($p = 0.034$ and $p < 0.01$, respectively, *Wald* test), whereas the difference in social welfare between *Ind* and *Res* is not significant ($p = 0.187$ and $p = 0.857$, respectively, *Wald* test). In terms of the comparison between *Res* and *Unr*, *Res* generates significantly higher social welfare only when the entry cost is high ($p < 0.01$, *Wald* test).

[27] See Table B-7 in Appendix B for summary statistics.

[28] The social welfare generated by an auction in the complete information setting is equal to V_1 the sum of auction revenue V_2 and the winning bidder's profit $V_1 - V_2$. Controlling for the drawn value of V_1 in columns 1-4 of Table 7 and for $V_1 - V_2$ in columns 5-8 eliminate welfare variations caused by the variation in random draws across treatments.

Table 7: Social welfare and bidders' profit: Panel regressions

	Social welfare				Bidders' profit			
	Model 1		Model 2		Model 1		Model 2	
	Low cost	High cost	Low cost	High cost	Low cost	High cost	Low cost	High cost
Unr(Cons.)	157.2***	114.1***	-27.12***	-59.05***	0.962	7.025	-13.36***	-26.91***
	(5.320)	(5.478)	(3.125)	(4.192)	(3.760)	(6.919)	(4.360)	(8.049)
Res	0.304	2.154	2.038	12.05***	15.81***	4.275	15.84***	6.381
	(7.523)	(7.604)	(2.544)	(3.671)	(5.318)	(9.785)	(5.177)	(9.539)
Ind	3.083	9.479	5.397**	11.39***	10.30*	-15.31	8.623*	-12.92
	(7.523)	(7.604)	(2.544)	(3.667)	(5.318)	(9.785)	(5.184)	(9.540)
V_1			1.000***	0.950***				
			(0.0139)	(0.0175)				
$V_1 - V_2$							0.909***	1.805***
							(0.150)	(0.234)
Obs.	720	720	720	720	720	720	720	720
Groups	4	4	4	4	72	72	72	72

Note: Model 1 and Model 2 are both panel regressions, while model 2 further controls for the highest value in the group (V_1) in social welfare and controls for the difference between the highest value and the second-highest value in the group $(V_1 - V_2)$in bidders' profit. Standard errors are in the parenthesis. *** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

Columns five to eight in Table 7 present the panel regressions of the bidders' profit, where $V_1 - V_2$ is added to control for variations in random draws across treatment in Model 2. The results do not change fundamentally between Model 1 and Model 2. When the entry cost is low, the bidders in *Ind* and *Res* on average earn a similar profit ($p = 0.164$, *Wald* test) but earn 8.62 and 15.84 units more profit compared to bidders in *Unr* ($p = 0.096$ and $p = 0.002$, respectively, *Wald* test). When the entry cost is high, the bidder's profits are not significantly different between either *Res* and *Unr* ($p = 0.504$, *Wald* test) or *Ind* and *Unr* ($p = 0.176$, *Wald* test). However, bidders in *Ind* treatment on average gain 19 units less profit than bidders in *Res* treatment ($p = 0.043$, *Wald* test). Recall that we previously observed much higher participation than predicted in *Ind* in the *high-cost* condition. Although a lower *participation effect* results in higher auction revenue, it does so at the expense of bidders' profits, leaving no statistical difference in social welfare between *Ind* and *Res*.

Result 6. *Compared to the Unr treatment, social welfare is higher in Ind treatment regardless of the cost condition, and is also higher in Res treatment when entry cost is high. Furthermore, there*

is no significant difference between the Ind and Res treatments under both cost conditions. Bidders make more profit in Ind and Res than in Unr when the entry cost is low. The bidders make a similar amount of profit in Res and Unr, but significantly lower profit in Ind than in Res when entry cost is high.

5 Conclusion

In this paper, we use the experimental method and a supporting theoretical framework to study entry restrictions and indicative bidding in auctions with costly entry. We document a trade-off from restricting entry; it increases participation but creates inefficiencies stemming from the selection process. These inefficiencies are amplified by off-equilibrium entry decisions and prevent the restricted entry mechanism from outperforming the unrestricted entry mechanism when the entry cost is high.

Our results show that indicative bidding generally increases the seller's revenue, but the gains come from greater participation rather than more efficient selection and occur at the expense of bidders' profits. Thus, while indicative bidding can be effective for revenue, successful implementation should also help potential bidders sort by expected values—a goal shared by sellers and bidders. One potential route is via a multi-step screening process rather than a single, simultaneous message choice; see Sweeting and Bhattacharya (2015). Future experimental work could test how such sequential screening affects participation, selection and welfare.

References

Aradillas-López, A., Gandhi, A. and Quint, D.: 2013, Identification and inference in ascending auctions with correlated private values, *Econometrica* **81**(2), 489–534.

Bhattacharya, V., Roberts, J. W. and Sweeting, A.: 2014, Regulating bidder participation in auctions, *The RAND Journal of Economics* **45**(4), 675–704.

Boone, A. L. and Mulherin, J. H.: 2007, How are firms sold?, *The Journal of Finance* **62**(2), 847–875.

Boone, J., Chen, R., Goeree, J. K. and Polydoro, A.: 2009, Risky procurement with an insider bidder, *Experimental Economics* **12**(4), 417.

Boone, J. and Goeree, J. K.: 2009, Optimal privatisation using qualifying auctions, *The Economic Journal* **119**(534), 277–297.

Bulow, J. and Klemperer, P.: 2009, Why do sellers (usually) prefer auctions?, *American Economic Review* **99**(4), 1544–75.

Chen, D. L., Schonger, M. and Wickens, C.: 2016, otree—an open-source platform for laboratory, online, and field experiments, *Journal of Behavioral and Experimental Finance* **9**, 88–97.

Cox, J. C., Dinkin, S. and Swarthout, J. T.: 2001, Endogenous entry and exit in common value auctions, *Experimental Economics* **4**, 163–181.

Fujishima, Y., McAdams, D. and Shoham, Y.: 1999, Speeding up ascending-bid auctions, *IJCAI*, Vol. 99, Citeseer, pp. 554–563.

Gentry, M. and Stroup, C.: 2019, Entry and competition in takeover auctions, *Journal of Financial Economics* **132**(2), 298–324.

Hansen, R. G.: 2001, Auctions of companies, *Economic Inquiry* **39**(1), 30–43.

Ivanova-Stenzel, R. and Salmon, T. C.: 2008, Revenue equivalence revisited, *Games and Economic Behavior* **64**(1), 171–192.

Kagel, J. H. and Levin, D.: 1990, *Auctions: a survey of experimental research'*, University of Pittsburgh.

Kagel, J. H. and Levin, D.: 2011, Auctions: A survey of experimental research, 1995-2010, *Handbook of experimental economics* **2**, 563–637.

Kagel, J. H. and Levin, D.: 2016, Auctions: A survey of experimental research, *The handbook of experimental economics* **2**, 563–637.

Kagel, J., Pevnitskaya, S. and Ye, L.: 2008, Indicative bidding: An experimental analysis, *Games and Economic Behavior* **62**(2), 697–721.

Khadem, N.: 2020, Shortlist of four suitors in the running to take over virgin australia, *ABC News* . Accessed June 29, 2025.
URL: *https://www.abc.net.au/news/2020-05-18/shortlist-of-four-suitors-to-take-over-virgin-australia/12258458*

Levin, D. and Smith, J. L.: 1994, Equilibrium in auctions with entry, *The American Economic Review* pp. 585–599.

Li, T. and Zheng, X.: 2009, Entry and competition effects in first-price auctions: theory and evidence from procurement auctions, *The Review of Economic Studies* **76**(4), 1397–1429.

Lu, J.: 2009, Auction design with opportunity cost, *Economic Theory* **38**, 73–103.

Lu, J.: 2010, Entry coordination and auction design with private costs of information acquisition, *Economic Inquiry* **48**(2), 274–289.

Lu, J. and Ye, L.: 2013, Efficient and optimal mechanisms with private information acquisition costs, *Journal of Economic Theory* **148**(1), 393–408.

Lu, J., Ye, L. and Feng, X.: 2021, Orchestrating information acquisition, *American Economic Journal: Microeconomics* **13**(4), 420–465.

Menezes, F. M. and Monteiro, P. K.: 2000, Auctions with endogenous participation, *Review of Economic Design* **5**(1), 71–89.

Milgrom, P. R.: 2004, *Putting auction theory to work*, Cambridge University Press.

Moreno, D. and Wooders, J.: 2011, Auctions with heterogeneous entry costs, *The RAND Journal of Economics* **42**(2), 313–336.

Palfrey, T. R. and Pevnitskaya, S.: 2008, Endogenous entry and self-selection in private value auctions: An experimental study, *Journal of Economic Behavior & Organization* **66**(3-4), 731–747.

Perry, M., Wolfstetter, E. and Zamir, S.: 2000, A sealed-bid auction that matches the english auction, *Games and Economic Behavior* **33**(2), 265–273.

Quint, D. and Hendricks, K.: 2018, A theory of indicative bidding, *American Economic Journal: Microeconomics* **10**(2), 118–51.

Roberts, J. W. and Sweeting, A.: 2013, When should sellers use auctions?, *American Economic Review* **103**(5), 1830–61.

Samuelson, W. F.: 1985, Competitive bidding with entry costs, *Economics letters* **17**(1-2), 53–57.

Sweeting, A. and Bhattacharya, V.: 2015, Selective entry and auction design, *International Journal of Industrial Organization* **43**, 189–207.

Ye, L.: 2007, Indicative bidding and a theory of two-stage auctions, *Games and Economic Behavior* **58**(1), 181–207.

Appendix A Equations and Proofs

Equations

Given an entry mechanism with $\overline{M} = 1$ the expected revenue of the auction is

$$\Pi(\mathcal{M}, \mathcal{X}) = \sum_{k=2}^{N} q_k \left(\alpha_0 + \frac{\min\{n,k\} - 1}{\min\{n,k\} + 1} (\bar{S} - \alpha_0) + \mathbb{E}[T] \right), \tag{4}$$

where α_0 is determined by (1) and $q_k = \binom{N}{k} \left(\frac{\bar{S}-\alpha_0}{\bar{S}}\right)^k \left(\frac{\alpha_0}{\bar{S}}\right)^{N-k}$ is the probability that k potential bidders choose $m = 1$. The expected revenue of the counterfactual scenario is

$$\hat{\Pi}(\alpha_0(\mathcal{M}), \mathcal{X}) = \sum_{k=2}^{N} q_k \left(\alpha_0 + \frac{k-1}{k+1} (\bar{S} - \alpha_0) + \mathbb{E}[T] \right), \tag{5}$$

and the *participation* and *selection effects* are given by

$$PE(\mathcal{M}, \mathcal{X}) = \frac{N-1}{N+1} \bar{S} + \mathbb{E}[T] - \sum_{k=2}^{N} q_k \left(\frac{2\alpha_0}{k+1} + \frac{k-1}{k+1} \bar{S} + \mathbb{E}[T] \right), \text{ and} \tag{6}$$

$$SE(\mathcal{M}, \mathcal{X}) = \sum_{k=n+1}^{N} q_k \left(\frac{k-1}{k+1} - \frac{n-1}{n+1} \right) (\bar{S} - \alpha_0). \tag{7}$$

For an entry mechanism with $\overline{M} = 2$ the revenue is

$$\begin{aligned} \Pi(\mathcal{M}, \mathcal{X}) = & \sum_{k=2}^{N} q_{k,0} \left(\alpha_0 + \frac{\min\{n,k\} - 1}{\min\{n,k\} + 1} (\alpha_1 - \alpha_0) + \mathbb{E}[T] \right) \\ & + \sum_{k=1}^{N-1} q_{k,1} \left(\alpha_0 + \frac{\min\{n-1,k\}}{\min\{n-1,k\} + 1} (\alpha_1 - \alpha_0) + \mathbb{E}[T] \right) \\ & + \sum_{j=2}^{N} \sum_{k=0}^{N-j} q_{k,j} \left(\alpha_1 + \frac{\min\{n,j\} - 1}{\min\{n,j\} + 1} (\bar{S} - \alpha_1) + \mathbb{E}[T] \right), \end{aligned} \tag{8}$$

where $q_{k,j} = \binom{N}{j}\binom{N-j}{k} \left(\frac{\bar{S}-\alpha_1}{\bar{S}}\right)^j \left(\frac{\alpha_1-\alpha_0}{\bar{S}}\right)^k \left(\frac{\alpha_0}{\bar{S}}\right)^{N-j-k}$ is the probability that j bidders choose $m = 2$ and k others choose $m = 1$.

The revenue of the counterfactual situation and the *participation effect* are the same as

in the $\overline{M} = 1$ case.

The *selection effect* with $\overline{M} = 2$ is given by

$$SE(\mathcal{M}, \mathcal{X}) = \sum_{k=n+1}^{N} q_{k,0} \left(\frac{k-1}{k+1} - \frac{n-1}{n+1} \right) (\alpha_1 - \alpha_0) + \sum_{k=n}^{N-1} q_{k,1} \left(\frac{k}{k+1} - \frac{n-1}{n} \right) (\alpha_1 - \alpha_0)$$
$$+ \sum_{j=n}^{N} \sum_{k=0}^{N-j} q_{k,j} \left(\frac{j-1}{j+1} - \frac{n-1}{n+1} \right) (\bar{S} - \alpha_1) \tag{9}$$

where $q_{k,j} = \binom{N}{j} \binom{N-j}{k} \left(\frac{\bar{S}-\alpha_1}{\bar{S}} \right)^j \left(\frac{\alpha_1-\alpha_0}{\bar{S}} \right)^k \left(\frac{\alpha_0}{\bar{S}} \right)^{N-j-k}$.

Given an entry mechanism with $\overline{M} = 1$ the expected aggregate profit of the bidders is

$$Y(\mathcal{M}, \mathcal{X}) = \sum_{k=2}^{N} q_k \left(\frac{(\bar{S} - \alpha_0)}{\min\{k, n\} + 1} - \min\{k, n\} c \right) + q_1 \left(\frac{\bar{S} + \alpha_0}{2} - c + \mathbb{E}[T] \right). \tag{10}$$

For $\overline{M} = 2$ the aggregate profit of the bidders is

$$Y(\mathcal{M}, \mathcal{X}) = \sum_{k=2}^{N} q_{0,k} \left(\frac{\alpha_1 - \alpha_0}{\min\{k, n\} + 1} - \min\{k, n\} c \right) + \sum_{k=1}^{N-1} q_{1,k} \left(\frac{\bar{S} - \alpha_0}{\min\{k, n\}} - \min\{k, n\} c \right)$$
$$+ \sum_{j=2}^{N} \sum_{k=0}^{N-j} q_{j,k} \left(\frac{\bar{S} - \alpha_1}{\min\{j, n\} + 1} - \min\{j, n\} c \right) + (q_{0,1} + q_{1,0}) \left(\frac{\bar{S} + \alpha_0}{2} - c + \mathbb{E}[T] \right). \tag{11}$$

Proof of Lemma 1

Given $\overline{M} = 1$, for any $n = 2, \ldots, N$ the cutoff signal α_0 is uniquely determined by (1). Uniqueness follows from arguments provided in the online appendix of Quint and Hendricks (2018) that hold for the environments used here. The LHS of this equation is continuous in α_0, is negative when $\alpha_0 = 0$ and is positive for $\alpha_0 = \bar{S}$ whenever $c < \bar{S} + \mathbb{E}[T]$. Then the LHS must cross zero exactly once from below. For $n', n \in \{2, \ldots, N\}$ and $n' > n$ the LHS is strictly smaller for n' than for n for every $\alpha_0 \in (0, \bar{S})$. Then the LHS must cross zero at an $\alpha_0' > \alpha_0$.

Proof of Proposition 1

From Lemma 1, for each $n \in \{2, \ldots, N\}$ there is a unique cutoff signal $\alpha_0(n)$ where $\alpha_0(n') > \alpha_0(n)$ for $n' > n$. Because the equilibrium messaging strategy is a cutoff strategy and T is a common component to all potential bidders values, the *participation effect* is equal to the expected loss in revenue from when the second highest valued bidder opts out of the auction. For a given draw of signals, this loss is $S_{(2)} + \mathbb{E}[T]$ where $S_{(2)}$ is the second highest drawn signal.

Given $n < n'$ consider two events that partition the possible draws of N signals. First, if $S_{(2)} \in (\alpha_0(n), \alpha_0(n'))$, the bidder with the second highest signal would opt in when the cap on bidders is n, but opt out when the cap is n'. Given this event, the *participation effect* will be lower under entry restriction n. In the complement of this event, both levels of entry restriction would lead to the same entry choice of the bidder with the second highest signal and therefore lead to the same *participation effect*. The *participation effect* is therefore higher under n' than n.

From (7), the *selection effect* can be written as $SE(\mathcal{M}, \mathcal{X}) = \sum_{k=0}^{N} q_k f(n, \alpha_0; k)$ where $f(n, \alpha_0; k) = 0$ for $k = 0, \ldots, n$ and $f(n, \alpha_0; k) = \left(\frac{k-1}{k+1} - \frac{n-1}{n+1}\right)(\bar{S} - \alpha_0)$ for $k = n+1, \ldots, N$. From Lemma 1, for $n', n \in \{2, \ldots, N\}$ and $n' > n$ the cutoff signal is higher: $\alpha_0(n') > \alpha_0(n)$. Then $f(n', \alpha_0(n'); k) \leq f(n, \alpha_0(n); k)$ for all k, and the inequality is strict for $k \geq n+1$.

Recall that $q_k(n) = \Pr(K = k)$ for $K \sim \text{Bin}(N, p(n))$ with $p(n) = \frac{\bar{S} - \alpha_0(n)}{\bar{S}}$. For $n' > n$, denote $q_k(n') = \Pr(K' = k)$ for $K' \sim \text{Bin}(N, p(n'))$ and note that $p(n') = \frac{\bar{S} - \alpha_0(n')}{\bar{S}} < p(n)$. Because $p(n') < p(n)$, the distribution of K' is first-order stochastically dominated by that of K. Since $f(n', \alpha_0(n'); k)$ is weakly increasing in k, we obtain

$$\sum_{k=0}^{N} q_k(n') f(n', \alpha_0(n'); k) \leq \sum_{k=0}^{N} q_k(n) f(n', \alpha_0(n'); k) < \sum_{k=0}^{N} q_k(n) f(n, \alpha_0(n); k).$$

The *selection effect* is therefore lower under n' than n.

Proof of Proposition 2

(a) Given that the total revenue loss is the sum of the *participation effect* and the *selection effect*, to show the result we will show that for sufficiently small c, the difference $SE((n, \overline{M} = 1), \mathcal{X}) - SE((N, \overline{M} = 1), \mathcal{X})$ is larger than $PE((n, \overline{M} = 1), \mathcal{X}) - PE((N, \overline{M} = 1), \mathcal{X})$ for all $n = \{2, \ldots, N-1\}$. Given that $SE((N, \overline{M} = 1), \mathcal{X}) = 0$, the difference in *selection effect* is equal to $SE((n, \overline{M} = 1), \mathcal{X})$, which from (7) is

$$SE((n, \overline{M} = 1), \mathcal{X}) - SE((N, \overline{M} = 1), \mathcal{X}) = \sum_{k=n+1}^{N} q_k \left(\frac{k-1}{k+1} - \frac{n-1}{n+1} \right) (\bar{S} - \alpha_0),$$

where α_0 and therefore q_k depend on both n and c. For any $n \in \{2, \ldots, N-1\}$, $\alpha_0 \to 0$ as $c \to 0$. Then $q_k = \binom{N}{k} \left(\frac{\bar{S} - \alpha_0}{\bar{S}} \right)^k \left(\frac{\alpha_0}{\bar{S}} \right)^{N-k} \to 0$ for $k < N$ and $q_N \to 1$. Then the difference in *selection effect* continuously approaches $\left(\frac{N-1}{N+1} - \frac{n-1}{n+1} \right) \bar{S}$ which is strictly positive for all $n < N$.

From (6) as $c \to 0$ and therefore $\alpha_0 \to 0$ and $q_k \to 0$ for $k < N$ and $q_N \to 1$, it follows that for $n \in \{2, \ldots, N\}$, $PE((n, \overline{M} = 1), \mathcal{X}) \to 0$ as $c \to 0$. Then the difference in *participation effect* approaches zero and is less than the difference in *selection effect* for all $n \in \{2, \ldots, N-1\}$.

(b) For a given $\varepsilon > 0$, let $c = \bar{S} + \mathbb{E}[T] - \varepsilon$ and $\alpha_0(\varepsilon) = \bar{S} - \delta(\varepsilon)$. Substituting these into (1) we get

$$p_0(\varepsilon - \delta(\varepsilon)) - c \sum_{k=1}^{N-1} p_k \min \left\{ 1, \frac{n}{k+1} \right\} = 0. \tag{12}$$

For $\varepsilon < \bar{S} + \mathbb{E}[T]$, $c > 0$ and therefore the first term of (12) is positive, which implies that $\delta(\varepsilon) \in (0, \varepsilon)$. It follow that as $c \to \bar{S} + \mathbb{E}[T]$, both $\varepsilon \to 0$ and $\delta(\varepsilon) \to 0$.

Using this we quantify the impact of changing n on $\delta(\varepsilon)$ for small ε. We can approximate the cutoff condition for $\delta(\varepsilon)$ close to zero using a Taylor expansion of the p_k terms.

Below we highlight terms of a order greater than or equal to $\delta^2(\varepsilon)$.

$$p_0 = \left(\frac{\alpha_0}{\bar{S}}\right)^{N-1} = \left(1 - \frac{\delta(\varepsilon)}{\bar{S}}\right)^{N-1} = 1 - \frac{(N-1)\delta(\varepsilon)}{\bar{S}} + \frac{(N-1)(N-2)\delta^2(\varepsilon)}{2\bar{S}^2} + o(\delta^2(\varepsilon))$$
$$p_1 = \binom{N-1}{1}\left(\frac{\delta(\varepsilon)}{\bar{S}}\right)\left(1 - \frac{\delta(\varepsilon)}{\bar{S}}\right)^{N-2} = \frac{(N-1)\delta(\varepsilon)}{\bar{S}} - \frac{(N-1)(N-2)\delta^2(\varepsilon)}{\bar{S}^2} + o(\delta^2(\varepsilon))$$
$$p_2 = \binom{N-1}{2}\left(\frac{\delta(\varepsilon)}{\bar{S}}\right)^2\left(1 - \frac{\delta(\varepsilon)}{\bar{S}}\right)^{N-3} = \frac{(N-1)(N-2)\delta^2(\varepsilon)}{2\bar{S}^2} + o(\delta^2(\varepsilon))$$

Any p_k for $k \geq 3$ is $o(\delta^2(\varepsilon))$.

Substituting in the Taylor expansions to (12) for $n = 2$ gives

$$\left(1 - \frac{(N-1)\delta}{\bar{S}} + \frac{(N-1)(N-2)\delta^2}{2\bar{S}^2}\right)(\varepsilon - \delta) = c\left(\frac{(N-1)\delta}{\bar{S}} - \frac{2(N-1)(N-2)\delta^2}{3\bar{S}^2}\right) + o(\delta^2).$$

For $n \geq 3$, the cutoff type will be selected to enter the auction with probability 1 instead of $2/3$ when two other bidders opt in. This is reflected by the coefficient on p_2 taking the value of 1 instead of $2/3$. In this case, substituting the Taylor expansions gives

$$\left(1 - \frac{(N-1)\tilde{\delta}}{\bar{S}} + \frac{(N-1)(N-2)\tilde{\delta}^2}{2\bar{S}^2}\right)(\varepsilon - \tilde{\delta}) = c\left(\frac{(N-1)\tilde{\delta}}{\bar{S}} - \frac{(N-1)(N-2)\tilde{\delta}^2}{2\bar{S}^2}\right) + o(\tilde{\delta}^2),$$

where we use the $\tilde{\delta}$ to indicate when the cutoff for when $n \geq 3$. If only the terms of order δ are considered, then there is no difference in the conditions. Therefore the difference of the cutoff signal from changing $n = 2$ to $n \geq 3$ is of order δ^2 and we denote $\delta - \tilde{\delta} = \mathcal{O}(\delta^2)$. We use this fact to compare the relative size of the changes in the *participation effect* and *selection effect* from increasing $n = 2$ to $n \geq 3$.

From (6) and substituting in $\delta(\varepsilon) = \bar{S} - \alpha_0(\varepsilon)$, the change in the *participation effect* is

$$PE((n,1),\mathcal{X}) - PE((2,1),\mathcal{X}) = g(\delta) - g(\tilde{\delta}),$$

where $g(\delta) = \sum_{k=2}^{N} q_k(\delta)\left(\bar{S} - \frac{2\delta}{k+1} + \mathbb{E}[T]\right)$ and $q_k(\delta) = \binom{N}{2}\left(\frac{\delta}{\bar{S}}\right)^k\left(1 - \frac{\delta}{\bar{S}}\right)^{N-k}$. It follows that

$g(\delta) = (\bar{S} + \mathbb{E}[T])\frac{N(N-1)}{2}\frac{\delta^2}{\bar{S}^2} + \mathcal{O}(\delta^3)$ and the difference in participation effect is

$$g(\delta) - g(\tilde{\delta}) = \frac{N(N-1)}{2}\frac{\bar{S} + \mathbb{E}[T]}{\bar{S}^2}\left(\delta^2 - \tilde{\delta}^2\right) + \mathcal{O}(\delta^3, \tilde{\delta}^3).$$

Since $\delta^2 - \tilde{\delta}^2 = (\delta - \tilde{\delta})(\delta + \tilde{\delta})$ its order is $\mathcal{O}(\delta^2) \cdot \mathcal{O}(\delta) = \mathcal{O}(\delta^3)$. Then the order of the change in *participation effect* is also $\mathcal{O}(\delta^3)$.

From Proposition 1 we know that the *selection effect* decreases as n increases for a given environment. So the change in *selection effect* can be bounded by the *selection effect* of $n = 2$:

$$|SE((n,1),\mathcal{X}) - SE((2,1),\mathcal{X})| < SE((2,1),\mathcal{X}) = \sum_{k=3}^{N} q_k(\delta)\left(\frac{k-1}{k+1} - \frac{1}{3}\right)\delta.$$

The probability that 3 potential bidders opt in is

$$q_3 = \binom{N}{3}\left(\frac{\delta}{\bar{S}}\right)^3\left(1 - \frac{\delta}{\bar{S}}\right)^{N-3} = \frac{N(N-1)(N-2)}{6}\left(\frac{\delta}{\bar{s}}\right)^3 + \mathcal{O}(\delta^4),$$

and all q_k for $k \geq 4$ are $o(\delta^3)$. Then the *selection effect* for $n = 2$ can be written as

$$\sum_{k=n+1}^{N} q_k\left(\frac{k-1}{k+1} - \frac{n-1}{n+1}\right)\delta = \frac{N(N-1)(N-2)}{36}\left(\frac{\delta^4}{\bar{S}^3}\right) + \mathcal{O}(\delta^5) = \mathcal{O}(\delta^4),$$

Therefore the change in *selection effect* from $n = 2$ to any $n > 2$ is at most of the order of δ^4. This implies that the decrease in the *participation effect* is of higher order than the increase in *selection effect* from restricting entry from $n > 2$ to $n = 2$. Therefore, for sufficiently high cost of entry that is less than $\bar{S} + \mathbb{E}[T]$, restricting entry to $n = 2$ will increase the expected revenue of the auction.

Proof of Proposition 3

Let $\alpha_1 \in [0, \bar{S}]$ be given. For all $\alpha_0 < \alpha_1$, $p_0 = p_{0,0}$ and $p_t = \sum_{j+k=t} p_{k,j}$ for $t = 1, \ldots, N-1$. In the following, we show that $\min\left\{1, \frac{n-j}{k+1}\right\} \leq \min\left\{1, \frac{n}{t+1}\right\}$ for $t = j + k$ and that the inequality is strict when $n < j + k + 1$.

When $n \geq j + k + 1$, then $\min\left\{1, \frac{n-j}{k+1}\right\} = 1$ and $\min\left\{1, \frac{n}{k+j+1}\right\} = 1$. Then for $k + j = t$

and $n \geq t+1$, $\min\left\{1, \frac{n-j}{k+1}\right\} = \min\left\{1, \frac{n}{t+1}\right\}$.

When $n \leq j+k+1$ and $j+k=t$, then $\min\left\{1, \frac{n-j}{k+1}\right\} = \frac{n-j}{k+1}$ and $\min\left\{1, \frac{n}{t+1}\right\} = \frac{n}{k+j+1}$. Then the difference in these fractions is

$$\frac{n-j}{k+1} - \frac{n}{k+j+1} = \frac{(n-j)(k+j+1) - n(k+1)}{(k+j+1)(k+1)} = \frac{nj - j(k+j+1)}{(k+j+1)(k+1)} \leq 0.$$

The last inequality follows from $n \leq j+k+1$ and is strict when $n < j+k+1$. It follows that for any $\alpha_1 \in [0, \bar{S}]$

$$c\sum_{k=1}^{N-1} p_k \min\left\{1, \frac{n}{k+1}\right\} \geq c\sum_{j=0}^{n-1}\sum_{k=1}^{N-1-j} p_{k,j} \min\left\{1, \frac{n-j}{k+1}\right\}. \tag{13}$$

It follows that the second term of (1) is less negative than the second term of (2) for any fixed α_0. Moreover, each of these terms becomes less negative as α_0 increases (see argument in the proof of Proposition 2). Because the first term of each equation is the same for any α_0 and $\alpha_1 < \bar{S}$, and the terms increase in α_0, the value of α_0 that satisfies (1) is higher than the α_0 that satisfies (2). Whenever $\alpha_1 < \bar{S}$ it follows that $p_{k,j} > 0$ for some j, k where $n < j+k+1$ and therefore the inequality of (13) is strict. This implies that α_0 is strictly lower when $\overline{M} = 2$ than when $\overline{M} = 1$. The *participation effect* only depends on the two-stage mechanism through its equilibrium value of α_0. Moreover, it is decreasing in α_0 (see (6)) and therefore, it is strictly less when $\overline{M} = 2$ than when $\overline{M} = 1$.

Appendix B Additional results

Table B-1: Panel regressions on auction revenue

	Model 1		**Model 2**	
	Low cost	High cost	Low cost	High cost
Unr (Cons.)	156.3***	107.1***	-10.22	-33.88***
	(5.74)	(7.44)	(7.15)	(18.12)
Res	-15.51*	-2.12	-13.90***	5.65
	(8.12)	(10.52)	(5.21)	(9.27)
Ind	-7.22	24.79**	-3.31	25.37***
	(8.12)	(10.52)	(5.21)	(9.27)
V_{2nd}			0.94***	0.84***
			(0.03)	(0.04)
Round			1.46**	0.24
			(0.71)	(1.02)
# of Obs.	720	720	720	720
# of Groups	72	72	72	72

Note: Both Model 1 and Model 2 use panel regressions, while model 2 further controls for the second-highest value in the group (V_{2nd}) and the time trend (i.e. Round). *** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table B-3: Predicted revenue, *participation* and *selection effects* given drawn signals

	Low cost (c=5)			**High cost (C=25)**		
	Unr	**Res**	**Ind**	**Unr**	**Res**	**Ind**
$\Pi_{Pred}(\mathcal{M}, \mathcal{X})$	153.93	145.69	150.02	101.80	104.83	106.84
$\hat{\Pi}_{Pred}(\alpha_0(\mathcal{M}), \mathcal{X})$	153.93	155.97	154.85	101.80	106.86	109.00
$\Pi_{Pred}(\mathcal{X}_0)$	168.5	166.79	164.34	163.58	154.32	162.88
Participation effect	14.57	10.82	9.50	61.78	47.46	53.89
Selection effect	0	10.28	4.83	0	2.04	2.15

Note: $\Pi_{Pred}(\mathcal{M}, \mathcal{X})$ is the expected revenue given the signal drawn in the experiment. $\hat{\Pi}_{Pred}(\alpha_0(\mathcal{M}), \mathcal{X})$ is the expected revenue in the counterfactual scenario where all potential bidders who send a positive entry message enter the auction stage. $\Pi_{Pred}(\mathcal{X}_0)$ is the auction revenue when there is no entry cost or entry restrictions. '*Participation effect*' is the difference between $\Pi_{Pred}(\mathcal{X}_0)$ and $\hat{\Pi}_{Pred}(\alpha_0(\mathcal{M}), \mathcal{X})$, and '*Selection effect*' is the difference between $\hat{\Pi}(\alpha_0(\mathcal{M}), \mathcal{X})$ and Revenue.

Table B-2: Panel regressions: *participation effect* and *selection effect*

	Participation effect				*Selection effect*			
	Model 1		Model 2		Model 1		Model 2	
	Low cost	High cost	Low cost	High cost	Low cost	High cost	Low cost	High cost
Unr (Cons.)	18.54***	62.20***	11.30**	32.23*	-0	-0	-2.101	-0.266
	(2.86)	(6.64)	(5.71)	(17.17)	(1.645)	(0.947)	(2.037)	(2.249)
Res	-3.62	-13.57	-3.60	-11.98	16.18***	6.999***	16.22***	7.124***
	(4.05)	(9.39)	(4.04)	(9.46)	(2.326)	(1.340)	(2.298)	(1.333)
Ind	-7.89*	-29.13***	-7.85*	-29.01***	12.68***	7.546***	12.77***	7.555***
	(4.05)	(9.39)	(4.04)	(9.45)	(2.326)	(1.340)	(2.298)	(1.332)
V_{2nd}			0.01	0.17***			0.022***	0.014***
			(0.02)	(0.04)			(0.006)	(0.005)
Round			0.99*	0.12			-0.302**	-0.125
			(0.57)	(0.95)			(0.139)	(0.122)
Obs.	720	720	720	720	720	720	720	720
Groups	12	12	12	12	12	12	12	12

Note: Model 1 and Model 2 are both panel regressions at the group level, while model 2 further controls for the second-highest value in the group (v_{2nd}) and the time trend variable "Round". Standard errors are in the parenthesis. *** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table B-4: Observed revenue, *participation* and *selection effects*

	Low cost			**High cost**		
	Unr	**Res**	**Ind**	**Unr**	**Res**	**Ind**
$\Pi_{Obs}(\mathcal{M},\mathcal{X})$	156.25	140.75	149.04	107.10	104.98	131.89
$\Pi_{EB}(\mathcal{M},\mathcal{X})$	149.96	135.68	141.37	101.37	98.68	124.86
$\hat{\Pi}_{Obs}(\alpha_0(\mathcal{M}),\mathcal{X})$	149.96	151.87	153.69	101.37	105.68	129.81
$\Pi_{Pred}(\mathcal{X}_0)$	168.5	166.79	164.34	163.58	154.32	162.8833
Participation effect	18.54	14.92	10.65	62.21	48.64	33.0733
Selection effect	0.01	17.39	13.73	0.00	7.64	7.28

Note: $\Pi_{Obs}(\mathcal{M},\mathcal{X})$ is the mean observed revenue in the experiment. $\Pi_{EB}(\mathcal{M},\mathcal{X})$ is calculated by replacing observed bids with equilibrium bids in the auction stage, and further accounts for revenue fluctuations caused by the random tie-breaking in *Res* and *Ind* by calculating the expected revenue of the auction given the observed participants' entry choice. $\hat{\Pi}_{Obs}(\alpha_0(\mathcal{M}),\mathcal{X})$ is the counterfactual scenario where all potential bidders who send a positive entry message enter the auction stage. $\Pi_{Pred}(\mathcal{X}_0)$ is the auction revenue when there is no entry cost or entry restrictions. '*Participation effect*' is $\Pi_{Pred}(\mathcal{X}_0) - \hat{\Pi}_{Obs}(\alpha_0(\mathcal{M}),\mathcal{X})$, and '*Selection effect*' is $\hat{\Pi}_{Obs}(\alpha_0(\mathcal{M}),\mathcal{X}) - \Pi_{EB}(\mathcal{M},\mathcal{X})$. The impact of overbidding on observed profits is $\Pi_{Obs}(\mathcal{M},\mathcal{X}) - \Pi_{EB}(\mathcal{M},\mathcal{X})$.

Table B-5: Panel regression: expected auction revenue given observed entry choice

	Model 1		Model 2	
	Low cost	High cost	Low cost	high cost
Unr (Cons.)	150.0***	101.4***	-13.05***	-31.02***
	(5.405)	(6.999)	(4.574)	(8.582)
Res	-14.28*	-2.687	-12.62***	4.806
	(7.643)	(9.898)	(3.925)	(8.803)
Ind	-8.592	23.49**	-4.570	24.05***
	(7.643)	(9.898)	(3.926)	(8.797)
v_{2nd}			0.967***	0.809***
			(0.0216)	(0.0361)
Observations	720	720	720	720
Number of groups	12	12	12	12

Note: Expected revenue is calculated by replacing observed bids with equilibrium bids in the auction stage, and accounts for revenue fluctuations caused by the random selection in *Res* and *Ind* by calculating the expected revenue of the auction given the observed participants' entry choice. It is the same expected revenue used to calculate the participation and *selection effect*. Model 1 and Model 2 are both panel regressions at the group level, while Model 2 further controls for the second-highest value in the group (v_{2nd}). Standard errors are in the parentheses. *** Significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table B-6: Entry choice breakdown

	Low cost (c=5)						**High cost (c=25)**					
	Unr		**Res**		**Ind**		**Unr**		**Res**		**Ind**	
	No.	Perct.	No.	Perct.	No.	Perct.	No.	Perct.	No.	Perct.	No.	Perct.
Nash Entry	**931**	**78%**	**917**	**76%**	**625**	**52%**	**990**	**83%**	**958**	**80%**	**632**	**53%**
0	405	34%	313	26%	260	22%	668	56%	597	50%	514	43%
1	526	44%	604	50%	134	11%	322	27%	361	30%	118	10%
2					231	19%						
Under Entry	**132**	**11%**	**141**	**12%**	**111**	**9%**	**99**	**8%**	**95**	**8%**	**86**	**7%**
(0,1)	132	11%	141	12%	97	8%	99	8%	95	8%	86	7%
(0,2)					8	0.6%						
(1,2)					6	0.4%						
Over Entry	**137**	**11%**	**142**	**12%**	**464**	**39%**	**111**	**9%**	**147**	**12%**	**482**	**40%**
(1,0)	137	11%	142	12%	89	7%	111	9%	147	12%	116	10%
(2,0)					80	7%					93	8%
(2,1)					295	25%					273	22%
N	1200		1200		1200		1200		1200		1200	

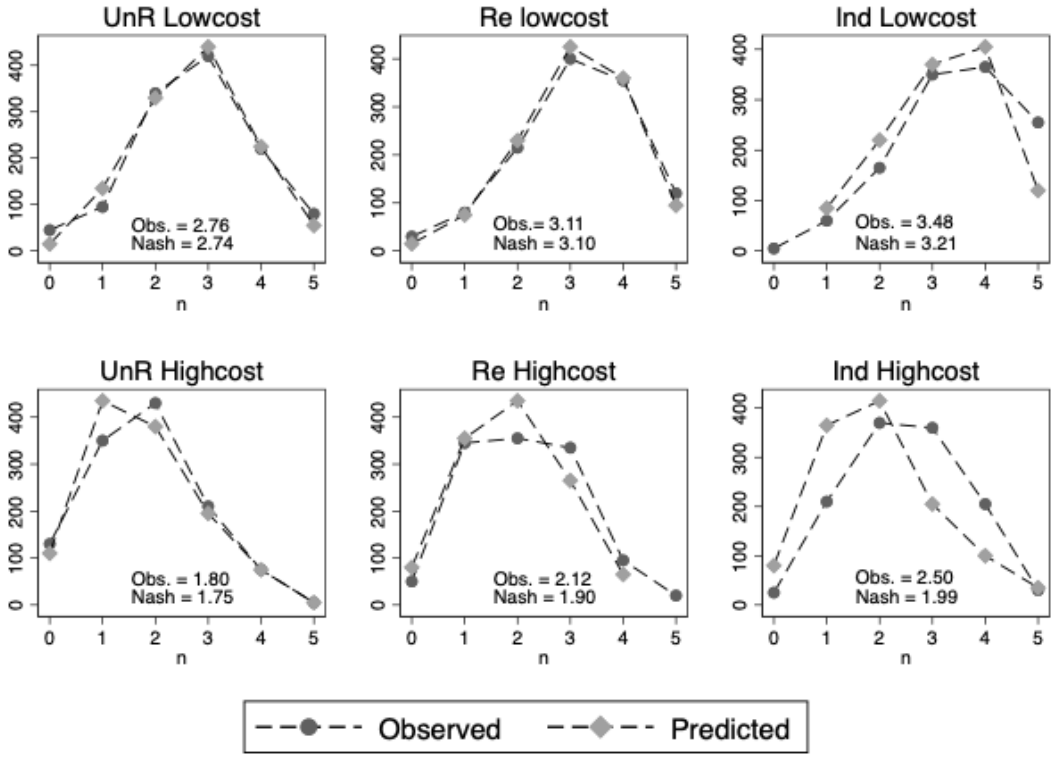


Figure B-1: Frequency of the average number of participants chose to enter

Table B-7: Bidders' profit: summary statistics

	Low cost			High cost		
Unr	**Obs**	**Predicted**	**NE**	**Obs**	**Predicted**	**NE**
	0.96	14.50	15.71	7.03	24.19	12.07
	(60.20)	(52.09)		(102.98)	(102.96)	
Res	**Obs**	**Predicted**	**NE**	**Obs**	**Predicted**	**NE**
	16.77	20.92	20.95	11.3	17.57	14.27
	(58.86)	(45.75)		(90.92)	(86.01)	
Ind	**Obs**	**Predicted**	**NE**	**Obs**	**Predicted**	**NE**
	11.26	21.32	17.16	-8.29	21.88	14.27
	(55.61)	(48.02)		(82.83)	(93.16)	

Note: Predicted bidders' profit is the expected bidders' profit based on the drawn values in the experiment. NE is the theoretical expected bidders' profit (not based on drawn values). Standard deviations are in the parenthesis.

Table B-8: Social welfare: summary statistics

	Low cost			High cost		
Unr	**Obs**	**Predicted**	**NE**	**Obs**	**Predicted**	**NE**
	157.22	168.43	167.10	114.12	125.99	121.96
	(77.106)	(71.73)		(82.3233)	(82.54)	
Res	**Obs**	**Predicted**	**NE**	**Obs**	**Predicted**	**NE**
	157.5207	166.6	167.74	116.275	122.40	131.09
	(81.458)	(78.14)		(76.5157)	(76.74)	
Ind	**Obs**	**Predicted**	**NE**	**Obs**	**Predicted**	**NE**
	160.3	171.34	172.02	123.6	128.72	131.09
	(74.201)	(71.22)		(75.653)	(79.26)	

Note: Predicted social welfare is the expected social welfare based on the drawn values in the experiment. NE is the theoretical expected social welfare (not based on drawn values). Standard deviations are in the parenthesis.

Appendix C Instructions

Welcome to our experiment! You will receive 30 RMB for showing up on time. Please read these instructions carefully and completely. Properly understanding the instructions will help you make better decisions and hence earn more money. The experiment will last about 1.5 hours. Your payoff in this experiment will be measured in experimental currency (i.e., EC). At the end of the experiment, we will convert your payoff in EC to cash and pay you in private. The exchange rate is 1 EC = 1.5 RMB.

Your total payment from this experiment will be the sum of:
(1) Your show-up fee: 30 RMB;
(2) Your payoff in this experiment;

Please keep in mind that you are not allowed to communicate with other participants during the experiment. If you do not obey this rule you will be asked to leave the laboratory. Whenever you have a question, please raise your hand; an experimenter will come to assist you.

Your task

At the beginning of the experiment, you will be given 30 EC as your initial endowment. In this experiment, there are 20 rounds in total. Before round 1, you will be randomly assigned to a group of 5 players and will stay in this group for the first 10 rounds. In round 11, you will be randomly reassigned to a new group of 5 players and stay in that group for the rest of the experiment. The computer will randomly assign letters from A to E to each of you as your player label and this assignment changes in every round. You will only be competing against the participants in your group.

In each round, you will participate in an auction. The auction takes place in two stages: in stage 1, you decide if you would like to enter stage 2 or not; in stage 2, (if you enter successfully,) you choose how much to bid in the auction. Your total valuation towards the asset that you are bidding for is composed of two parts: You will get the first part of

your valuation in stage 1 before you make the entry decision; then you will get the second part of your valuation in stage 2 before you enter your bid if you enter the auction.

Stage 1: Entry decision

The computer first randomly draws an integer from 1 to 100 (including 1 and 100) for each participant independently. Each integer has 1% chance to be drawn. You only observe your own draw. This number reveals the first part of your valuation towards the asset that you are bidding for in stage 2. After seeing this information, you need to make a decision on whether or not to enter the auction stage based on this partial information you have about your total valuation for the asset. You can choose 1 of the 3 options to indicate your willingness to enter: "0" (Do Not Enter), "1" and "2" (both represent enter with 2 giving you a higher entry priority than 1).

The number of entrants in each group in the auction stage is restricted to at most 2. If the number of players that choose either "1" or "2" is equal or less than 2, then all participants who choose "1" or "2" are selected to enter automatically. However, if there are more than 2 participants in your group choosing to enter, a selection process will apply. First we randomly select up to two players from those who chose "2". Then, if less than 2 players have been selected, we randomly select the remaining entrants from those who chose "1".

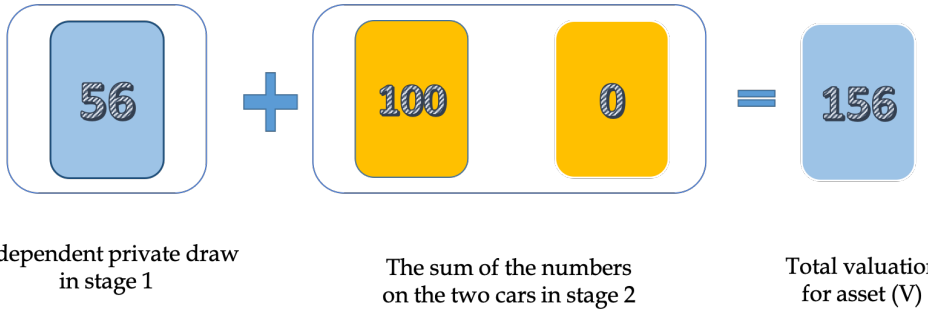
The selected entrant(s) will proceed to stage 2 and an entry fee will be charged. **Notice that the entry fee is 5 EC in Round 1-10, and then increases to 25 EC in Round 11-20.** If you are not selected, no entry fee will apply, and you do not need to make any more decisions in this round.

Stage 2: Auction stage

In this stage, all the entrants first see two cards on the screen. Each of the cards has two possible values, 0 and 100. The computer will randomly assign one of the values (0, or 100 with equal chance) independently to each card. The sum of the two numbers assigned to the two cards is the second part of your the asset valuation, which is the same for all entrants. There are four possible scenarios: both cards have 0; the first card is 0 and the second card is 100; the first card has 100 and the second card has 0; both cards have 100.

Hence, the second part of the value shared by all entrants could be 0 EC with 25% chance, 100 EC with 50% chance, and 200 EC with 25% chance.

Each entrant's full valuation for the asset (V) is calculated as the sum of the first part of the valuation revealed in stage 1 (i.e., the independent private draw between 1-100) and the second part of the valuation (i.e., the sum of the numbers on the two cards which are drawn for each group) shared by all entrants revealed in stage 2. In the example below, if an entrant's draw in the first stage is 56, and then the computer assigned 100 and 0 to two cards in stage 2 respectively, his/her total valuation for the asset is 56+(0+100)=156.



After learning your total valuation, all the entrants need to bid for the asset. The entrant with the highest bid in your group will win the asset. The winner will pay an amount equal to the second highest bid. If there is a tie for the highest bid, a winner will be randomly selected among these bidders. In this case, the second highest bid is the same as the highest bid. When there is only one entrant, that player wins the asset and pays zero (i.e. the second highest bid).

Your payoff

Your payoff for each round will be calculated at the end of auction as the following:

- If you do not enter stage 2: your payoff = 0
- If you choose to enter and are selected:
  - If you lose, your payoff= - entry fee

- If you win, your payoff= your total valuation - the second highest bid - entry fee

Summary

You will play 20 rounds of this 2-stage auction game. You will be randomly assigned to a group of 5 participants twice during this experiment (first before round 1 and again before round 11). In each round, you decide whether to enter the auction or not and how much to bid. Your valuation for the asset in each round is determined by the sum of your independent draw (revealed in stage 1) and the common draw given to all entrants in stage 2. At the end of each round, all group members' entry decisions, two parts of the valuation information, entrants' bids and payoffs will be displayed to you, regardless of whether you chose to enter stage 2 or not. See a screenshot of this page below:

	Player A	Player B	Player C	Player D	Player E (You)
First signal	58 EC	73 EC	22 EC	93 EC	57 EC
Entry choice	1	1	2	2	0
Second value	-	-	0 EC	0 EC	-
Total valuation (V)	-	-	22 EC	93 EC	-
Bid	-	-	25 EC	20 EC	-
Win/Lose	-	-	Win	Lose	-
payoff	0 EC	0 EC	22 EC- 20 EC-5 EC= - 3 EC	0 - 5 EC= - 5 EC	0 EC

In addition, a history table which gives information about entry decisions and winner's payoffs from previous rounds is provided.

Your total payment

After you complete all 20 rounds, the computer will randomly draw 1 round to pay you. Your total payoff from the experiment will be your endowment (30 EC) plus your payoff in the drawn round. Your total payoff will then be converted into cash and paid to you together with your show-up fee (30 RMB) at the end of today's session.

Other information

To further ensure that everyone in this lab understands the game properly, you will need to answer several control questions that are constructed based on the information given out in these instructions. The experiment will start once all of you have answered these questions correctly. Please do not hesitate to ask for help if you have any questions regarding the information provided in our instructions or the control questions we ask you to answer.

At the end of today's experiment, you will also need to fill out a small post-experimental questionnaire, including some demographic information (e.g., your gender, age, major...) and your decisions in the experiment. All the information you provide will be kept anonymous and is strictly confidential. The only purpose of collecting this information from you is for academic research analysis.

Thank again for your participation and patience! The experiment will start soon...