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Why are open ascending auctions popular?

The role of information aggregation and behavioral biases*

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Abstract

The popularity of open ascending auctions is often attributed to the fact that openly observable bidding allows to aggregate dispersed information. Another reason behind the frequent utilization of open auction formats may be that they activate revenue enhancing biases. In an experiment, we compare three auctions that differ in how much information is revealed and in the potential activation of behavioral biases: (i) the ascending Vickrey auction, a closed format; and two open formats, (ii) the Japanese-English auction and (iii) the Oral Outcry auction. Even though bidders react to information conveyed in others' bids, information aggregation fails in both open formats. In contrast, the Oral Outcry raises higher revenue than the other two formats, by stimulating bidders to submit unprofitable jump bids and triggering a quasi-endowment effect.

Keywords ascending auctions, information aggregation, jump bidding, auction fever

JEL Codes D44, D82, C90

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1 Introduction

Open ascending auctions are routinely preferred to sealed-bid formats by both private platforms (e.g., Amazon, eBay, Catawiki) and policy makers, for example in the allocation of spectrum rights (Milgrom, 1989; McMillan, 1994; Milgrom, 2004). One compelling theoretical reason for their popularity is that open ascending auctions allow bidders to endogenously aggregate dispersed information due to the observability of the bids. Standard theory predicts information aggregation to have two advantages: It allows for a more precise estimate of the value and it leads to higher revenues in expectations. In single-unit auctions with affiliated values, buyers who are better informed bid more aggressively (Milgrom and Weber, 1982). This is implied by the linkage principle, according to which average revenues are increased by providing bidders with more information about the value of the item for sale. To this date, the linkage principle remains highly influential and is often cited as the reason why open auctions are and should be preferred over sealed-bid formats.¹

Empirically, however, it remains an open question whether open ascending auctions are indeed capable of aggregating information. One challenge is that the single-unit setup with affiliated values hosts multiple equilibria (Bikhchandani et al., 2002). This multiplicity may impede information aggregation (Milgrom, 2004, p. 197). Another challenge is that some open ascending auctions allow for jump bidding, which may obfuscate information (Avery, 1998; Ettinger and Michelucci, 2016). Also, in every-day auctions, particularly those involving non-professional bidders, the reasoning required to infer information from the bidding of others may be too demanding.

Aside from their potential for information aggregation, open ascending auctions may also differ from closed formats in the extent to which they activate or mitigate behavioral biases. Some of these biases provide alternative mechanisms for raising revenues. For instance, it is common for open ascending auctions to provisionally award the item during the auction to the bidder who submits the highest standing

¹In 2018, the German Bundesnetzagentur motivated their design for the next 5G multi-unit spectrum auction in the following way: “The auction proceeds as an open auction, which means that the bidders receive, in each auction round, information about the bids of other bidders. This allows bidders to estimate other bidders’ valuations of spectrum blocks during the auction. As the intermediate auction result is observable for all bidders, they can adjust their bidding strategy accordingly. In this way they can reduce the risks of overestimating the actual value of spectrum blocks and overpaying for the spectrum blocks (winner’s curse-risk)” (Bundesnetzagentur, 2018). Theoretically, the reduction in uncertainty about the value in open auctions may lead to a lower probability that the winner pays more than the value and to higher revenue, as more precise information allows for more aggressive bidding.

bid. As a result, auction fever may be activated, which encourages overbidding and leads to a quasi-endowment effect (Heyman et al., 2004; Ehrhart et al., 2015). Another possibility is that open ascending auctions encourage naïve jump bidding, for instance when bidders are impatient and want to terminate the auction quickly. In contrast to when jump bidding is motivated by strategic reasons, naïve jump bidding may easily enhance revenues.² Open ascending auctions may also encourage spiteful bidding because bidders can condition their overbidding on the presence of other remaining active bidders (Andreoni et al., 2007; Bartling et al., 2016). There is, however, also a possibility that open ascending auctions mitigate behavioral biases. For example, the higher transparency of open formats may lead to buyers becoming aware of the winner’s curse and tame the overbidding (Levin et al., 1996). When the winner’s curse is mitigated, lower revenue may be the result in an open ascending auction.

In this paper we explore whether open auctions do raise higher revenues than sealed-bids formats. Moreover, we disentangle whether this is due to information being successfully aggregated or other behavioral mechanisms.

eBay provides a natural setting to explore information aggregation and revenues in open auctions. eBay uses an open ascending format which allows for jump bidding and provisionally awards the good to the highest standing bidder. Thus, both information aggregation and revenue-enhancing biases are possible in this format. We collected eBay data for one of the most frequently auctioned cellphones at the time of the study. The field-data analysis that we report in the Appendix, Section A.1, offers suggestive evidence that information endogenously generated during the auction (proxied by the price reached halfway through the auction) and jump bidding (proxied by the average increment per bidder) correlate positively with final prices. On the basis of a median split, we find that above median bidding in the first half of the auction corresponds to an increase of 67% in the final price. Likewise, with a median split on the average increment per bidder, we find above median increments between consecutive bids correspond to an increase of 14% of the final price. The findings are consistent with information aggregation and also with the presence of revenue-enhancing naïve jump bidding. However, such data has severe limitations. First, the direction of causality is un-

²Probably the most preposterous auction ever was decided by a naïve jump bid. After murdering the Roman emperor Pertinax (A.D. 193), the praetorian guard offered the Roman empire for sale in an ascending auction. Julianus topped Sulpicianus’ highest bid of 20,000 sesterces per soldier by a winning bid of 25,000 sesterces. The winning bid corresponded to 5 years of wage of each of the 10,000 praetorians. After Julianus defaulted on his bid, he was murdered after a reign of only 66 days (Klemperer and Temin, 2001).

clear. Second, such data is lacking crucial insights about bidders' information and the value of the item for sale, which makes it impossible to separate behavioral mechanisms from information aggregation. Third, we miss data from an appropriate control condition, i.e., a counterfactual auction which does not allow for information aggregation.

To overcome these limitations, we employ a laboratory experiment where we randomly assign subjects to three different auction formats. These differ in the information revealed during the bidding process, and, possibly, also in the extent to which different behavioral biases can be triggered. To ensure comparability, all formats use a second-price rule.

The first auction format is the Japanese-English auction, an open ascending auction with irrevocable exits. In this format, a clock tracks the ascending price and bidders withdraw from the auction until a single bidder remains, who wins the auction and pays the last exit price. The exit prices of other buyers are publicly observed. These bids then allow to infer other bidders' private signals, which are informative about the common value.

The second auction format is the ascending Vickrey auction, a sealed-bid ascending auction. It is implemented identically to the Japanese-English auction with an ascending clock and irrevocable exits. However, exits are not observable by others, thereby eliminating the possibility of information aggregation.

The third format we run is the Oral Outcry auction, modeled to fit popular auction designs. It falls between the other two in terms of its potential for information aggregation. In this auction, bidders can control how much information is revealed. They can engage in the informative, incremental bidding that characterizes the Japanese-English auction. They can also engage in jump bidding, i.e. out-bid the standing bid by a non-negligible amount. Jump bidding can be used rationally, for instance to obfuscate information (Ettinger and Michelucci, 2016) or to signal to other bidders that it is better to back off (Avery, 1998). Jump bidding could also be used naïvely by impatient bidders. The Oral Outcry auction, while still allowing for information aggregation, may also be the most conducive to revenue-enhancing biases. This is the only format that allows bidders to submit naïve jump bids, and it is also the only format that can activate auction fever by provisionally awarding the good during the auction.

The comparison between the ascending Vickrey auction and the Japanese-English auction provides a clean comparison of the role of information aggregation, since these formats differ only in the public revelation of exits. Theoretically, rational bidders use the information revealed in the auction to form a more precise

estimate of the common value, which makes them less fearful of the winner’s curse (Milgrom and Weber, 1982). As a result, the Japanese-English auction is expected to raise higher revenue than the ascending Vickrey auction. Remarkably, this prediction is reversed if bidders are naïve and tend to fall prey to the winner’s curse. By gradually revealing the exit prices of bidders with low signals, the Japanese-English auction could make the risk of suffering from the winner’s curse more transparent, thus taming the overbidding and reducing revenues compared to the ascending Vickrey auction. This intuition is captured by signal averaging models, which we describe more precisely in Section 3.

When information is successfully aggregated, remaining bidders’ uncertainty about the common value is reduced and prices approximate the underlying common value more closely (Wilson, 1977; Kremer, 2002). We evaluate information aggregation by comparing the squared distance between the price and the common value across formats. We further decompose information aggregation into two components: (i) the extent to which bids are objectively informative of the common value (*information revelation*); and (ii) the extent to which bidders actually use this information effectively in their own bidding (*information processing*).

We find that in the Japanese-English auction, less information than expected is generated due to highly heterogeneous behavior in early dropouts. Some bidders with a low signal display spiteful behavior and stay in the auction longer than their more cooperative peers do. Such heterogeneity is not observable by the remaining bidders and degrades the quality of the revealed information. In addition, bidders are processing the available information sub-optimally. Even though bidders are responding appropriately to the fact that early bids are revealing little information by largely disregarding them, the potential to aggregate the information actually available is mostly not realized. Instead, the processing of information is qualitatively in agreement with signal averaging heuristics. This combination of noisy early bids and sub-optimal information processing leads to a failure of information aggregation. Although subjects have only access to their private information in the ascending Vickrey auction, more information is aggregated: the squared distance between prices and common value is lower in the ascending Vickrey than in the Japanese-English auction, in which additional information is available.

Surprisingly, bids in the Oral Outcry and Japanese-English auction reveal a similar amount of information about the common value. That is, bidders do not make extensive use of the potential to strategically hide their information via jump bidding. However, in the Oral Outcry auction, the available information is processed to an even smaller extent than in the Japanese-English auction. Here,

final bids are substantially distorted by the quasi-endowment effect and rash jump bidding. Subjects who are prone to endowment effects on a questionnaire measure tend to stay too long in the auction and earn substantially lower payoffs. Additionally, this auction encourages many bidders to submit unfounded jump bids. These forces result in systematic overbidding and a price which is the poorest predictor of the common value across our auction formats.

The interplay of all aforementioned factors leads to similar revenues in the Japanese-English auction and the ascending Vickrey auction. Highest revenues are observed in the Oral Outcry auction. The rationale for why the Oral Outcry auction is most often observed in the field may be quite different from the understanding in the theoretical and policy-oriented literature. Instead of leading to information aggregation, it triggers behavioral biases such as the quasi-endowment effect and reckless jump bidding.

In many ways, the laboratory provides the ideal environment to study how information is generated and processed. An important question is whether experimental results generalize to the field. Our experiments use non-professional bidders (students) that bid for objects with moderate values (of approximately €25). We think that this situation is representative for most online auctions in the field. Beyond everyday auctions involving consumers, some of our results may also extrapolate to some situations involving professional bidders. For instance, [Dyer et al. \(1989\)](#) find that professional bidders in the construction industry fall prey to the winner’s curse in the same way as students do. We do not claim that our results generalize to spectrum auctions where bidders seek the advice of game theorists.³

The remainder of the paper is organized in the following way. Section 2 reviews the literature, Section 3 presents the game and some theoretical benchmarks, Section 4 describes how information aggregation is evaluated. Section 5 presents the experimental design and procedures. Section 6 discusses the experimental results and Section 7 concludes.

³Nevertheless, it is interesting to note that also in those auctions bidders sometimes engage in bidding that is merely motivated to drive up the price for a competitor. Such bidding may be driven by a spiteful motivation, or by a predatory desire to weaken the competitor in a future market ([Levin and Skrzypacz 2016](#)). When bidding behavior may be driven by such considerations, it becomes very hard to infer valuable information from competitors’ bids.

2 Related literature

Previous laboratory studies have documented how people succumb to the winner’s curse in common value auctions. For an overview, see [Kagel and Levin \(2014\)](#). [Eyster and Rabin \(2005\)](#) and [Crawford and Iriberrí \(2007\)](#) present behavioral models to explain the winner’s curse. Recent studies have studied pathways behind the winner’s curse, highlighting that problems with contingent reasoning ([Charness and Levin, 2009](#)) and disentangling the importance of belief formation and non-optimal best responses ([Charness and Levin, 2009](#); [Ivanov et al., 2010](#); [Camerer et al., 2016](#); [Koch and Penczynski, 2018](#)). We compare whether open auctions mitigate or worsen the importance of behavioral biases such as the winner’s curse. [Levin et al. \(2016\)](#) find that a Dutch auction lessens a winner’s curse compared to sealed bid formats.

An important strand of literature investigates whether markets are capable of aggregating dispersed information. A series of experiments have investigated information aggregation in asset markets. Results have been mixed. [Plott and Sunder \(1988\)](#) find that information aggregation only occurs when preferences are homogeneous or when a complete set of contingent claims can be traded. [Forsythe and Lundholm \(1990\)](#) find that information aggregation only succeeds with trading experience and common knowledge of dividends. Hence, information aggregation seems to fail when the inference task is complicated by the presence of several dimensions of uncertainty, or when the information conveyed by prices in equilibrium is less naturally interpretable.

How information is processed is also studied in the context of auctions, a particularly important form of a market. Several papers study the effect of an auctioneer exogenously revealing information in auctions. [Kagel and Levin \(1986\)](#) and [Kagel et al. \(1995\)](#) show that there are ambiguous effects of revealing information in first-price and second-price sealed-bid auctions. In a setting with both private and common value elements, [Goeree and Offerman \(2002\)](#) find that high-quality reports of the auctioneer can positively affect efficiency and revenue, but to a lower extent than predicted by theory.⁴ In contrast to this work, our paper explores *endogenous* information aggregation. Aside from shedding light on revenue effects, we uncover the process of how bidding generates information in auctions, and how bidders process the available information.

Close to our work, [Levin et al. \(1996\)](#) compare the performance of the Japanese-

⁴[Dufwenberg and Gneezy \(2002\)](#) study another form of exogenous information disclosure. They find that the disclosure of losing bids after first-price sealed-bid common value auctions reduces revenue.

English auction and the first-price auction in a common value setting. They find that the revenue comparison of the Japanese-English auction and the first-price auction depends on the experience of the bidders: with inexperienced bidders the first-price auction raises more revenue. However, with experience this effect disappears and is sometimes reversed. By changing the price-rule and the auction format across treatments simultaneously, they cannot identify the effect that information aggregation has on the outcomes. Another difference to this paper is that [Levin et al. \(1996\)](#) adopt uniformly distributed values and signals, a knife-edge case where in equilibrium rational bidders will only process the *lowest* drop-out price and disregard all other exit decisions in the Japanese-English auction. More importantly, in their analysis they do not include the Oral Outcry auction which triggers the revenue enhancing biases that may explain their actual popularity.

A related literature compares different auction formats when bidders have interdependent valuations. In such environments, the linkage principle does not hold; with symmetric bidders, expected revenue and efficiency are predicted to be the same across auction formats ([Goeree and Offerman, 2003a](#)). Some experimental papers introduce specific asymmetries that break the revenue and efficiency equivalence results. For instance, [Kirchkamp and Moldovanu \(2004\)](#) compare efficiency between the Japanese-English and second-price sealed-bid auctions in a particular setup with interdependent values, where a bidder's value is the sum of the own private signal and one specific signal of the other bidders. In that setup, they find that the Japanese-English auction generates higher efficiency. [Boone et al. \(2009\)](#) and [Choi et al. \(2019\)](#) compare open and sealed-bid auctions with interdependent values in the presence of insiders, to whom the value of the item for sale is revealed. In line with their theoretical predictions, revenue and efficiency increases in the Japanese-English auctions.⁹ In contrast to this work, our paper sheds light on how bidders process information in the more common case where signals are affiliated. We investigate the case in which the linkage principle applies and information revelation occurs with symmetric bidders. As [Perry and Reny \(1999\)](#) note, “The linkage principle has come to be considered one of the

⁹“A different kind of interdependence is studied in the multi-unit auction experiments of [Betz et al. \(2017\)](#). They consider the sale of multi-unit private values emission certificates of this year (good A) and of next year (good B). Interdependence is created because units of type A can be used as type B unit, but not vice-versa. Their treatment variables are the type of auction and whether goods are auctioned sequentially or simultaneously. When items are auctioned simultaneously, they find that open ascending auctions are more efficient than sealed-bid auctions. Auctioning the items sequentially enhances the performance of sealed-bid auctions but leaves the efficiency of ascending auctions unaffected. In each auction format, total revenues are higher when items are sold sequentially.

fundamental lessons provided by auction theory.” Another distinction between our approach and this literature is that we study how information is aggregated directly, instead of by relying on comparative statics effects which are predicted by information aggregation. We do so by employing measures of information aggregation frequently used to theoretically evaluate information aggregation in auctions, see, for example, [Wilson \(1977\)](#), [Pesendorfer and Swinkels \(2000\)](#) and [Kremer \(2002\)](#). Our results show that although revenue is increased in some of our formats, this occurs while information aggregation *decreases*, opposite to the theoretical prediction.

We also contribute to the literature on the Oral Outcry auction. [Roth and Ockenfels \(2002\)](#) study the impact of different rules for ending internet auctions at eBay and Amazon on bidders’ propensity for late bidding. Amazon’s rule to extend bidding deadlines if new bids are submitted resembles our procedure. In the lab, [Ariely et al. \(2005\)](#) find that Amazon’s rule to extend bidding deadlines generates higher revenue than eBay’s in a private value setting. [Cho et al. \(2014\)](#) provide field evidence and show that in the comparison of two open auction formats, an open outcry English auction format raises more revenue, which they attribute to endogenous information revelation. It can however not be excluded that the higher revenue in the open outcry auction is actually due to behavioral factors. Close to our experiment, [Gonçalves and Hey \(2011\)](#) compare a Japanese-English and an Oral Outcry auction and find that they result in approximately equal revenue. However, they focus on auctions with only two bidders, which means that the potential of the Japanese-English auction to generate endogenous information is excluded by design.

Finally, we relate to the literature on endogenous information processing in stylized games. [Anderson and Holt \(1997\)](#) initiated a literature on informational cascades. [Eyster et al. \(2018\)](#) find that subjects’ social learning depends on the complexity of the underlying problem. [Magnani and Oprea \(2017\)](#) investigate why subjects violate no-trade theorems and find that over-weighting of one’s private information contributes to such violations. [Hossain and Okui \(2018\)](#) study how subject’s correlation neglect ([Enke and Zimmermann, 2019](#)) explains information processing. Other studies show that biased inference can arise in in-transparent problems where subjects display a lack of contingent reasoning ([Esponda and Vespa, 2014](#); [Ngangoue and Weizsacker, 2015](#); [Martínez-Marquina et al., forthcoming](#)). Our take-away from this literature is that subjects do pay attention to the behavior of others, but that their sophistication depends on specifics of the problem, such as the transparency of its presentation and its complexity. There

is no single result that generalizes across all contexts. In our view, this implies that social learning should be studied in the particular setup of interest. How information is processed and aggregated in the canonical affiliated values setup of [Milgrom and Weber \(1982\)](#) is therefore still an open question. While this setup not only inspired a vast body of theoretical work, it also was and continues to be very influential in advice on actual auction design ([McMillan \(1994\)](#), p. 151-152), [Bundesnetzagentur \(2018\)](#)).

3 Auction formats and theoretical benchmarks

In the following, we describe the auctions implemented in the laboratory, present Nash equilibria as well as behavioral heuristics and explain revenue predictions.

3.1 General setup: Bidders and payoffs

All our formats are common value auctions with five bidders and a second-price rule. The common value of the object for sale is unknown to bidders, who only receive a private signal about the value. More precisely, the good has value V , where $V \sim \mathcal{N}(\mu, \sigma_V) = \mathcal{N}(100, 25)$. Each bidder $i \in \{1, 2, \dots, 5\}$ receives a signal S_i of the common value V . This signal is the sum of the underlying value and an individual error ϵ_i :

$$S_i = V + \epsilon_i$$

This error is *i.i.d.* across bidders and normally distributed with mean 0 and standard deviation σ_ϵ : $\epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon) = \mathcal{N}(0, 35)$.

In all formats, the winner of the auction is the bidder who submits the highest bid. This bidder receives a payoff equal to V minus the second highest bid. All the other bidders receive a payoff of 0. For notational purposes, define X_i as the signal received by bidder i , $Y_{(k)}$ the k -th highest of the signals received by any other bidder $j \neq i$, so e.g. $Y_{(1)}$ is the highest signal received by any bidder other than bidder i .

3.2 Auction formats

We now provide details for each of the three auction formats we study.

The ascending Vickrey auction (AV)

We implement the ascending Vickrey auction (AV) with a clock procedure. After bidders have been privately informed of their signals, the price rises simultaneously from 0 for all participants. At any integer price $0, 1, 2, 3, \dots$, bidders can decide to leave the auction by pressing the “EXIT”-button. In the AV, no bidder observes whether any other bidder has left. The auction stops as soon as four bidders have exited the auction. The last remaining bidder wins the auction and pays the price at which the fourth bidder leaves. In case multiple bidders leave last at the same price, one of them is randomly selected to be the winner and pay the price at which she left.

The Japanese-English auction (JEA)

The Japanese-English auctions (JEA) makes use of the same clock procedure. Differently from the AV, all remaining bidders are notified in real time of other bidders' exit prices. Like in the AV, the winning bidder is the last remaining bidder after four bidders exit. This bidder pays the price at which the fourth bidder left the auction.

The Oral Outcry auction (OO)

In the Oral Outcry auction (OO) bidders can outbid each other repeatedly and by arbitrary amounts until no more out-bidding takes place and the good is awarded to the highest standing bidder. In our implementation, bidding proceeds in bidding rounds. In each bidding round, all bidders have 15 seconds to submit a maximum bid. As soon as one bid is submitted, the bidding round is interrupted. At this point, the bidder who submitted the highest bid becomes the standing bidder, the provisional winner in case the auction would stop afterwards. The current price is set to the second highest bid at this moment. A new bidding round starts, the clock is reset to 15 seconds and the standing bidder is excluded from submitting a new bid.⁶ During the auction, bidders are notified of the highest maximum bid of each of the other bidders, with the exception of the current standing bidder, about whom it is only revealed that her highest bid is at least as high as the current price. The auction ends as soon as the countdown elapses without further bidding. At this point, the last standing bidder wins the auction. She pays the last current price, which is the second highest bid at the end of the auction.

⁶This leads to an auction ending time being determined endogenously. Such a rule is a feature of online auctions at amazon.com, yahoo.com and catawiki.com.

3.3 Nash equilibrium predictions and behavioral forces

In this section, we use game theoretic results, behavioral theories and recent experimental findings to contextualize our research questions. We start with presenting the Nash equilibrium predictions, according to which the JEA should aggregate information and consequently lead to higher revenues than the AV.

AV and JEA: Nash Equilibria and the *Linkage Principle*

Symmetric Nash equilibria in single-unit auctions with affiliated values have been derived in [Milgrom and Weber \(1982\)](#). In the AV, a bidder's strategy can be described by a reservation price, which makes this format strategically equivalent to the standard second-price sealed-bid auction (see [Milgrom, 2004](#), p. 187-188). A symmetric equilibrium of the AV is given by bids $b_i(S_i)$:

$$b(S_i) = \mathbb{E} [V | X_i = S_i, Y_{(1)} = S_i]$$

That is, each bidder exits the auction as soon as the clock reaches the expected value of the good for sale conditional on her signal and assuming that the highest signal obtained by other bidders is also S_i .⁷

In the symmetric Nash equilibrium of JEA, bidders include endogenously revealed information into their bidding strategies. The first bid is given by (see [Milgrom and Weber, 1982](#)):

$$b_0(S_i) = \mathbb{E} [V | X_i = S_i, Y_{(1)} = S_i, \dots, Y_{(4)} = S_i]$$

Just like in the AV, the first exit bid is obtained via a conditional expectation, assuming that all other bidders hold an equally high signal. However, as soon as the first bidder drops out at p_1 , the remaining bidders perfectly infer the signal of the exiting bidder, from $p_1 = b_0(Y_{(4)})$. All bidders dropping out subsequently base their k -th bid (for $k > 1$) on their private information and the signals inferred from the $k - 1$ observed dropouts. The remaining bidders bid $b_k(S_i)$:

$$b_k(S_i) = \mathbb{E} [V | X_i = S_i, Y_{(1)} = S_i, \dots, Y_{(5-k-1)} = S_i, p_1 = b_0(Y_{(4)}), \dots, p_k = b_{k-1}(Y_{(5-k)})]$$

⁷In our experimental setup with 5 bidders and normally distributed values and signals, [Goeree and Offerman \(2003b\)](#) show that the above conditional expectation is equal to: $b(S_i) = \mathbb{E} [V | X_i = S_i, Y_{(1)} = S_i] = S_i - \frac{\int_{-\infty}^{\infty} \epsilon \phi_V(S_i - \epsilon) \phi_\epsilon^2(\epsilon) \Phi_\epsilon^3(\epsilon) d\epsilon}{\int_{-\infty}^{\infty} \phi_V(S_i - \epsilon) \phi_\epsilon^2(\epsilon) \Phi_\epsilon^3(\epsilon) d\epsilon}$, where $\phi_V(\cdot)$ denotes the pdf of the common value distribution, $\phi_\epsilon(\cdot)$ the pdf of the error distribution, with its cdf $\Phi_\epsilon(\cdot)$.

This equilibrium allows to iteratively back out all information except the one contained in the highest signal.⁸ According to the *linkage principle*, the information revealed in the JEA leads to more aggressive bidding, the fourth bid in the JEA is on average higher than the fourth bid in the AV (Milgrom and Weber, 1982). Bikhchandani et al. (2002) have identified other symmetric Nash equilibria that implement the same outcome. In such equilibria, the first three bidders drop out at a fraction $\alpha \in (0, 1)$ of the bids at which they dropped out before, and the last two bidders bid as before.⁹

AV and JEA: A behavioral perspective

Overbidding is often observed in experimental common value auctions, suggesting that in practice bids may not align well with Nash equilibrium predictions. Even in the AV, bidding in agreement with a symmetric equilibrium is quite sophisticated and requires bidders to (i) use their prior about the distribution of the value; (ii) account for the fact that the bidder with the highest signal is predicted to win the auction. Thus, to avoid the winner’s curse, bids need to be shaded.

Simpler behavioral rules have been proposed in alternative to Nash equilibrium bidding. For example, bidders in the AV who ignore both (i) and (ii), and only rely on their private signal, may adopt the “bid signal”-heuristic (Goeree and Offerman, 2003b): $b(S_i) = S_i$, which leads to expected overbidding.

The JEA, on the other hand, allows bidders to observe early exits of other bidders with low signals. This could make (ii), i.e., the fact that winning bidders receive higher signals than their peers, transparent to bidders in a natural way. The “bid signal”-heuristic remains available in the JEA. However, by raising awareness about the winner’s curse, the JEA can lead to less overbidding. The “signal averaging rule” proposed by Levin et al. (1996) captures this intuition. According to this rule, bidders bid an equally weighted average of their own signal and the signals of their fellow bidders, revealed from the previous dropouts. After k

⁸We determine Nash equilibrium bids in our setup, using a result by DeGroot (2005, p. 167). For inferred or assumed signal realizations of bidder i , $\bar{S} = \frac{1}{4} \sum_{j=1}^4 Y_{(j)} + X_i$:

$\mathbb{E}[V|X_i, Y_{(1)} \dots, Y_{(4)}] = \frac{\frac{\mu}{\sigma_V^2} + \frac{5\bar{S}}{\sigma_\epsilon^2}}{\frac{1}{\sigma_V^2} + \frac{5}{\sigma_\epsilon^2}} = \frac{5\bar{S}\sigma_V^2 + \mu\sigma_\epsilon^2}{5\sigma_V^2 + \sigma_\epsilon^2}$. On request, we provide derivations showing that equilibrium bids can be inverted such that they depend linearly on the signal and observed bids. This also applies to all other models considered in this paper. We therefore restrict ourselves to linear information use in all estimations.

⁹Bikhchandani and Riley (1991) study asymmetric Nash equilibria and show that they can lead to different revenue rankings than those established by Milgrom and Weber (1982). In our experiment, all bidders are treated symmetrically and there is nothing that facilitates coordination on an asymmetric equilibrium. In this sense, a symmetric equilibrium is more plausible.

bidders dropped out, with the vector of revealed signals being \mathbf{S}_j , this implies the following bid: $b_k(S_i, \mathbf{S}_j) = \frac{1}{k+1}S_i + \frac{1}{k+1} \sum_{j=1}^k S_j$.¹⁰ In expectation, the “signal averaging rule” corrects for the overbidding observed in the “bid signal”-heuristic. If bidders follow these two behavioral rules in the JEA and the AV respectively, then the former format is predicted to raise lower revenues.

Somewhat more sophisticated bidders could process information about the prior distribution of the value, and thereby accommodate (i), incorporating information on the prior. This would lead to slightly modified versions of the two rules above, the “Bayesian bid signal”-heuristic, and the “Bayesian signal averaging rule”. By anchoring bidding to the prior, these rules lead to less extreme under- and overbidding. However they continue to predict that the JEA raises lower revenues than the AV.

In the “Bayesian bid signal”-heuristic bidders bid the expected value of the good for sale, conditional on one’s signal: $b(S_i) = \mathbb{E}[V|S_i] = S_i - \mathbb{E}[\epsilon_i|S_i]$. Goeree and Offerman (2003b) show that $b(S_i) = \frac{\sigma_V^2 S_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$. According to the “Bayesian signal averaging rule”, bidders combine Bayes rule with the symmetric signal averaging rule.¹¹ After k observed dropouts, bidder i calculates the average of available signals $\bar{S} = \frac{1}{k+1}S_i + \frac{1}{k+1} \sum_{j=1}^k S_j$ and bids $b(\bar{S}) = \frac{\sigma_V^2 \bar{S} + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$.

Nash equilibrium predictions and predictions based on behavioral rules now lead to conflicting effects of information revelation on revenues. While private signals can be inferred in both types of benchmarks, revenue ranking predictions with the behavioral rules are driven by the degree to which bidders’ are made aware of the winners’ curse in the JEA relative to the AV.

Using our parameterization and draws, Table 1 summarizes the revenue predictions for the Nash Equilibrium and the behavioral models that we discussed.¹²

Table 1: Revenue predictions

	AV	JEa
Nash equilibrium	95.8	97.4
Bid signal	117.4	117.4
Signal averaging rule	117.4	91.1
Bayesian bid signal	105.9	105.9
Bayesian signal averaging	105.9	94.0

¹⁰Note that this rule can be plugged in iteratively, such that it depends only on the most recent dropout, which is an average of all revealed signals. This yields $b_k(S_i, b_{k-1}) = \frac{1}{k}S_i + \frac{k-1}{k}b_{k-1}$.

¹¹A peculiar feature of the setup of Levin et al. (1996) with uniformly distributed values and signals is that a Bayesian will form the same belief as a naïve bidder who ignores the prior. This is not the case in our setup with normally distributed values and errors.

¹²Note that the revenue prediction of a model only depend on the revenue-determining bidder using the particular model. Theoretically, in the JEA, bidders are able to infer all other bidders’ signals irrespective of the model these other bidders are using, as long as all bidders hold correct beliefs on which model others are using.

Nash equilibrium revenues are only slightly higher in the JEA than in the AV. This is not an artifact of our parameter choices. As we show in [Appendix Section A.1](#), similar minor revenue differences result for various combinations of variances of the values and errors. In both formats, the winners capture some information rents and make positive profits, as the price-determining bidder in equilibrium slightly underestimates the value by design of the equilibrium bidding strategies.

The differences in predictions for the behavioral models are much larger. Moreover, the behavioral rules yield losses for the winners in the AV. In the JEA, bidders make substantial profits if they use (Bayesian) signal averaging rules.¹³

The Oral Outcry: information aggregation and behavioral biases

The Oral Outcry auction format is very rich and there are no clear Nash equilibria for this format. Still, we can make some observations about the potential of the Oral Outcry for information aggregation and revenues. In this format, bidding may proceed incrementally as in the Japanese-English auction. That is, bidders may constantly be active until their reservation price is reached, which would allow for similar inference as in the JEA.

This format can also encourage jump bidding. From a strategic point of view, jump bidding can be used to signal a high estimated value of the item and deter other bidders from continuing to bid. [Avery \(1998\)](#) shows how strategic jump bidding can be supported in an equilibrium of a game that is much simpler than ours. Similarly, jump bidding may obfuscate information, as shown in a stylized auction game in [Ettinger and Michelucci \(2016\)](#). In either case, severe jump bidding suppresses information aggregation and its revenue-enhancing effects.

On the other hand, recent experimental findings suggest that some features in Oral Outcry may be particularly prone to revenue-enhancing behavioral biases, such as auction fever ([Heyman et al., 2004](#); [Ehrhart et al., 2015](#)). Similarly, jump bidding might not be used in the sophisticated way studied theoretically, e.g. it might rather be driven by bidders' impatience.

¹³Note that our experimental setup leads to low expected revenue with signal averaging-rules. This allows us to test the rules beyond what was possible in [Levin et al. \(1996\)](#). In their setup, signal averaging-rules lead to predictions more similar to Nash equilibrium revenues.

4 Information aggregation: Measure and benchmarks

When information is successfully aggregated, bidding and prices move closer to the underlying common value (Wilson, 1977; Kremer, 2002). We measure the degree of information aggregation with the squared distance between the price and the common value and compare it across formats (Hanson et al., 2006). A distance of 0 would imply perfect information aggregation in the sense that bidders inferred the exact true value.

The possibility of perfect inference is curtailed by the noisiness of the signals. We account for the maximal information potentially available, the one contained in the five signals, by computing the Full Information benchmark. In it, all five signals are revealed and bidders bid the conditional expected value of the item given these signals. Additionally, we model the lowest degree of aggregation with the No Information benchmark, where bidders bid the prior average common value, thus ignoring also their own private signal.

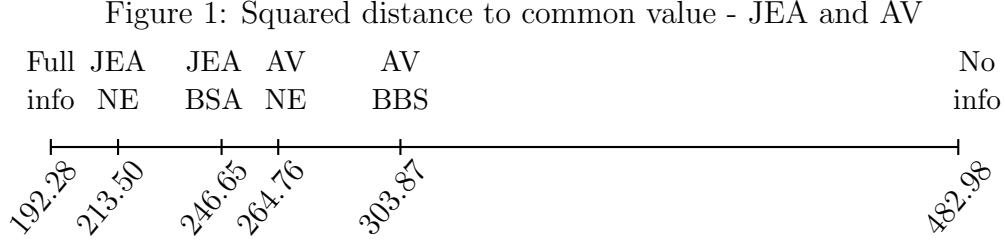
We illustrate the Full and No Information benchmark as the lower and upper bounds of a segment measuring information aggregation. On this segment, lower values indicate a better approximation of the common value by the price, hence improved information aggregation.

In the segment, we also show how much information aggregation is predicted in Nash equilibrium and by some exemplary behavioral models. In the Nash equilibrium of the JEA, we see that the Full Information benchmark is almost attained.¹⁴ In the Nash equilibrium of the AV, the squared distance to the common value is higher, as less information aggregation is possible. By comparing the Nash equilibrium predictions of the two formats, we see the theoretical impact of information aggregation: If dropouts are observable, bidders obtain a more precise estimate of the value and the price follows the common value more accurately.

The prediction that the JEA leads to higher information aggregation compared to the AV generalizes to the behavioral models of bidding behavior. The Bayesian bid signal heuristic (BBS) in the AV auctions predicts a larger dispersion around the common value compared to Bayesian signal averaging (BSA) in the JEA.¹⁵ Therefore, even when processing information in a sub-optimal manner, bidders are predicted to improve their estimate of the value when they observe others' bids.

¹⁴It is not fully attained for two reasons: (i) the bid determining the price is based on 4, rather than 5, signals; (ii) bidders maximize expected profit, with information rents for the winner.

¹⁵This also holds for the comparison of signal averaging- and bid signal-heuristics, which are omitted for brevity.



5 Experimental design and procedures

The computerized laboratory experiment was conducted in July and October 2018 at the CREED laboratory of the University of Amsterdam. In total, we ran 30 sessions with 10 subjects each. We preregistered this experiment (Offerman et al., 2019). Most subjects were students of business, economics or other social sciences, with 50.7% being male and an average age of 23. Each subject participated in only one session.

The experiment was conducted in a laboratory with soundproof cubicles. As a consequence, information revelation was entirely controlled as intended in the experimental design. In Appendix D, we present the instructions together with screenshots of the auction interface for all formats. Subjects read the computerized instructions at their own pace, and they had to correctly complete a set of test questions before they could proceed to the experiment. Before the experiment started, subjects received a handout with a summary of the instructions. At the end of the experiment, subjects filled out a brief questionnaire.

In the experiment, 30 auction rounds were played. Payment was based on five rounds randomly selected at the end of the experiment. Subjects earned points that were exchanged according to a rate of €0.25 for each point. Subjects earned on average €24.28 (standard deviation: 6.02, minimum earnings were set to €7) in approximately two hours.¹⁶

We run three between-subject treatments, each corresponding to one auction format. In each ten-subject session, subjects were randomly rematched into groups of five every round, therefore a matching group of 10 subjects coincides with the session size. Common values and corresponding signals were drawn before sessions started. Draws are *i.i.d.* across rounds for common values, and error draws are also *i.i.d.* across subjects. For the experiment, we use identical draws in the

¹⁶In the experiment, only one subject had a negative payment balance if calculating total earnings across *all* rounds. In the pre-registration, we announced that we also analyze our data without bankrupted subjects. However, excluding this one subject does not affect results.

identical order across treatments. Thus, treatment differences are not driven by differences in random draws. In the experiment, we truncate common value and signal draws between 0 and 200 and also only allow for bids between 0 and 200.¹⁷

We communicated the distributions of values and signals with the help of density plots and we allowed subjects to generate example draws for the common value and corresponding signals. At the start of each round in each auction, subjects were privately informed about their signals and the auction started as soon as all bidders in a session indicated that they were ready.

The rules of the auction formats were described in Section 3. The auction procedure was visualized with a thermometer. In the AV and the JEA, the price increased from 0 by one point every 650 milliseconds. Approximately three times per second, the program checked whether any bidder dropped out. In the JEA, bidders were shown the prices at which the first, second and third dropout occurred. After a dropout in this auction, there was a pause of four seconds where the price did not rise to allow the remaining bidders to process the information.

In all three treatments, at the end of each round all subjects were shown the price which the winner paid and the common value that was drawn. In each round, each bidder was endowed with 20 points, and the winning bidder was additionally paid the difference between the common value and the second highest bid. When negative, the difference was deducted.

In the 13 sessions ran in October 2018, we included two additional incentivized tasks at the end to investigate some conjectures developed after the first sessions. First, we used a measure adapted from Goeree and Yariv (2015) to elicit a subject's tendency to conform to others' choices in an environment where these choices contain no information. Subjects had an incentive to guess an unknown binary state. Their choice was to either receive a noisy but informative signal of the state, or to sample the uninformative decisions from three previous subjects. Crucially, these previous subjects had no access to any information about the true state, and subjects were made aware of this fact. Second, we obtained a measure of subjects' social preferences by using the circle test to measure their value orientation (Sonnemans et al., 2006). We included these measures to test some conjectures about the exit decisions of subjects with low signals in the Japanese-English auction. In addition, in the oral outcry auction we included two unincentivized questionnaire measures of subjects' tendency to succumb to endowment effects to further

¹⁷We discarded a set of draws whenever a common value or signal exceeded our bounds. This occurred for 0 out of 600 common value draws, and 121 out of 6000 drawn signals. Due to the small scale of this phenomenon, we ignore truncation in our analysis.

investigate the role of the quasi-endowment effect in this auction.¹⁸

Many features of our experimental design are motivated by the theoretical model with affiliated signals (Milgrom and Weber, 1982). The situation that we study is stylized, and our setup may offer more opportunities for learning than bidders would have outside of the laboratory when they bid on real commodities. In auctions outside of the laboratory, it may be much less clear to the winner that he suffered a loss, which may impede learning. In addition, our conjecture is that bidders may suffer more from endowment effects when they are bidding on a real commodity than when they are bidding on a fictitious good with induced value. From this perspective, we expect that biases may be larger outside of the laboratory.

6 Experimental results

In this section we present the experimental results. We first present an overview of the revenues generated in the three auctions. Next, we discuss information use in the Japanese-English auction (JEA). Then, we compare the level of information aggregation in all three formats. Finally, we present evidence on jump bidding and the quasi-endowment effect in the Oral Outcry auction (OO).

In our analysis, we use data from all 30 rounds. We present results on experienced bidders in the Appendix Section B.4. Results are mostly in line with the main analysis, otherwise we address this within the main text.

6.1 Revenue

Figure 2 and Table 2 present mean revenues by treatment.¹⁹ Average revenues are quite similar in the AV and the JEA, but are substantially larger in the OO. Differences are most pronounced in the first 15 rounds, but differences continue to be significant also for experienced bidders in the last 15 rounds. Table 2 also reports test results of comparisons of revenue across treatments together with test

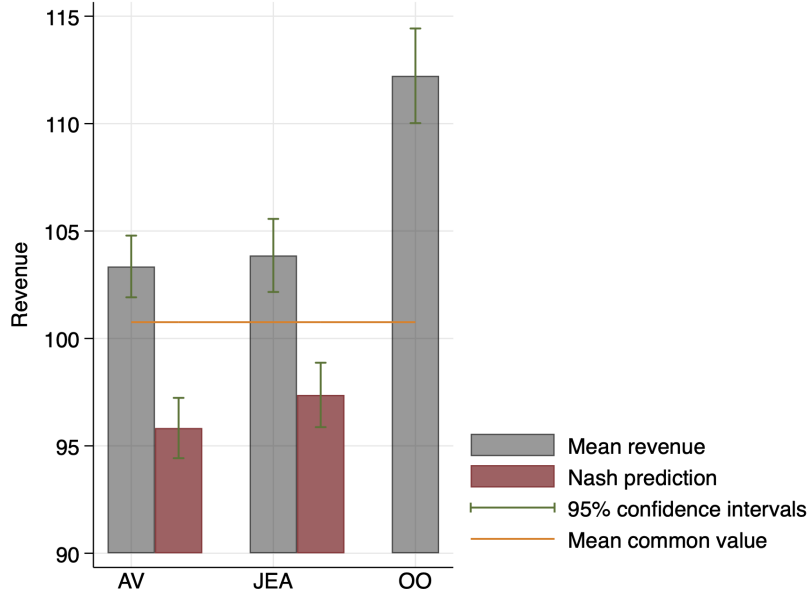
¹⁸Question 1 was: “Suppose you paid €30 for 5 cello lessons. After the first lesson you realize that you really don’t like it. How many of the remaining lessons do you attend? You cannot get the money back.” Question 2 was: “Suppose that tickets are on sale for the National Lottery to be played out in one week, with a prize of €100.000 and you just bought one ticket for €2.50. A colleague offers you money to buy the ticket from you. What is the minimum price at which you are willing to sell the ticket to him?”

¹⁹In one auction in the AV, the auction unintentionally ended after only three, not four, bidders dropped out. We remove the data from this particular auction.

results of the comparisons of revenues with the Nash benchmark.²⁰

We find strongly significant revenue differences between the OO and both other auction formats. Contrary to theoretical predictions, revenue does not differ significantly between the AV and the JEA. In both the AV and the JEA, actual revenues deviate systematically from the Nash benchmark.

Figure 2: Mean revenue, Nash equilibrium predictions and common values



One explanation for the revenue equivalence between the AV and the JEA is that bidders simply ignore the information that is revealed in the JEA. Another possibility is that the more transparent JEA activates different behavioral forces that offset each other. In the next section we explore these possible explanations.²¹

²⁰Treatment results are robust to using parametric tests and the non-significance of a treatment difference is not arising from comparing matching group averages. When regressing revenues on treatment dummies, clustering standard errors on a matching group-level (600 observations per treatment), we find that compared to a baseline of the AV, the dummy on the JEA is not significant with a p -value=.778, whereas the dummy on the OO is significant at a p -value=.005.

²¹In the preregistration plan, we announced that we would compare how well rational and behavioral models organize actual bidding. It turns out that none of the models comes even close to explaining the early dropouts in the auction. As a result, we have chosen to relegate this analysis to the [Appendix Section B.2](#)

Table 2: Revenue statistics by treatment

Round		Revenue		
		Mean (Standard deviation)		
		1-30	1-15	16-30
AV		103.4 (17.9)	106.1 (19.5)	100.6 (15.7)
JEA		103.9 (21.2)	106.5 (20.9)	101.3 (21.3)
OO		112.2 (27.5)	118.0 (31.2)	106.5 (21.7)
Round		Treatment effects: p-values		
		1-30	1-15	16-30
AV vs.	JEA	.597	.940	.734
	OO	.003	.011	.049
JEA vs.	OO	.009	.003	.059
Round		Revenue difference to Nash eq'm: p-values		
		1-30	1-15	16-30
AV vs.	Nash eq'm	.001	.002	.010
JEA vs.	Nash eq'm	.001	.000	.049

Notes: Mean and standard deviation of revenues by treatment, over time. Test results (p -values) of revenue comparisons across treatments and to the Nash equilibrium prediction. For each test, we use the averages per matching group as independent observations for the Mann-Whitney U-tests (MWU). This gives 10 observations per treatment.

6.2 Information processing in JEA

In contrast to the rational and some of the behavioral models' predictions, revenues do not differ systematically between the AV and the JEA. One explanation is that bidders in the JEA disregard the bidding of others and only use their private information. However, the data suggests that subjects do react to fellow participants' choices, as we now show that bids are correlated with earlier dropouts.

Table 3 presents the results of a fixed-effects regression analysis that models how bids correlate with available information. Define as $d_{i,j,g,t}$ the dropout price of bidder i at the j -th order, in group g and auction round t . For $j \in \{1, \dots, 4\}$:

$$d_{i,j,g,t} = \alpha + \beta s_{i,t} + \gamma \mathbf{d}_{j-1,g,t} + \delta t + \eta_i + \epsilon_{i,t}$$

where $s_{i,t}$ is the private signal of bidder i , $\mathbf{d}_{j-1,g,t}$ is a vector of $j - 1$ observed dropouts, t is the auction round. η_i is a bidder-specific fixed effect and $\epsilon_{i,t}$ is a bidder-round error.

Models (1) to (4) provide fixed effects estimates of drop-out prices regressed on available information, similar to the analysis by [Levin et al. \(1996\)](#). There is a recurring pattern in how subjects' bids correlate with available information:

Table 3: Bidders' use of information in JEA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$d_{i,1,g,t}$	$d_{i,2,g,t}$	$d_{i,3,g,t}$		$d_{i,4,g,t}$			$V_{g,t}$	\widehat{BR}
	Observed	Observed	Observed	Observed	Nash	SA	BSA		
$s_{i,t}$	0.294*** (0.057)	0.267*** (0.034)	0.172*** (0.027)	0.118*** (0.016)	0.287 (.)	0.250 (.)	0.168 (.)	0.250*** (0.020)	0.288*** (0.001)
$d_{1,g,t}$		0.372*** (0.035)	0.023 (0.018)	0.025 (0.015)	0.100 (.)	0 (.)	0 (.)	-0.009 (0.025)	0.032*** (0.003)
$d_{2,g,t}$			0.552*** (0.044)	-0.038 (0.037)	0.167 (.)	0 (.)	0 (.)	-0.003 (0.052)	0.060*** (0.003)
$d_{3,g,t}$				0.709*** (0.072)	0.333 (.)	0.750 (.)	0.832 (.)	0.291*** (0.070)	0.151*** (0.003)
t	-0.316 (0.281)	-0.122 (0.114)	-0.083 (0.074)	-0.075** (0.031)				0.295*** (0.073)	0.087*** (0.002)
Constant	35.185*** (8.628)	41.823*** (2.723)	32.049*** (2.933)	26.290*** (3.619)	11.265 (.)	0 (.)	0 (.)	41.882*** (3.799)	44.804*** (0.361)
Observations	600	600	600	600				600	600
Adj. R^2	0.119	0.491	0.756	0.817				0.362	0.996
Adj. R^2 absorb. i	0.425	0.592	0.768	0.821					
Rounds	1-30	1-30	1-30	1-30				1-30	1-30
Estimation	FE	FE	FE	FE				OLS	OLS

Notes: $d_{j,g,t}$: dropout at order j in group g and round t ; $V_{g,t}$: common value; $s_{i,t}$: signal of bidder i . (1) to (4) are fixed effects estimates (within estimation) of information use. Dependent variables are dropouts at each order, e.g. (1) are all bidders dropping out first in an auction. Regressors are the available information at each dropout. (5) to (7) show how information is used in three canonical models, only for the fourth dropout. SA refers to the signal averaging-rule, BSA to the Bayesian signal averaging-rule. Note that these show how bids respond to earlier bids, where these bids are also calculated to follow the theoretical models. (8) shows how the price-setting bidder would have to use information to predict the common value after observing three dropouts. (9) shows how the bidder dropping out fourth would weigh information in an empirical best response. We provide adjusted R^2 of the original within-estimated model, as well as from estimating standard OLS where we include subject-specific absorbing indicators. The latter also includes fit obtained from subject fixed effects. Standard errors in parentheses, clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Bidders' dropouts depend significantly only on their own signal and the just preceding dropout.²² The most recent dropout receives much more relative weight than bidders' signals. Thus, bids appear to respond quite strongly to the auction proceedings.²³

Note that this analysis does not provide direct evidence that bidders actively incorporate information. For example, bids may be correlated simply due to the correlation of the two underlying signals. To address this concern, in Table 14 in the Appendix, we compare the use of information to the benchmark provided in the AV, and provide further evidence that available information appears to be actively included in bids in the JEA. We show that bids in the JEA are more strongly correlated than in the AV, which suggests that bids do react actively to the revealed information.

All theoretical models considered in this paper process information linearly (derivations available on request).²⁴ In models (5) to (7), we provide theoretical benchmarks for the fourth dropouts, representing informational weights implied by these models. These models show how bids would react to (theoretical) earlier dropouts, and are purely theoretical, not estimated.²⁵ By comparing estimated information use to the use in these models we can evaluate whether bidding strategies are consistent with any of the models, which can be helpful to predict outcomes in other auction environments.

In model (5), Nash equilibrium, bidders do not ignore information from the first and second dropouts when they choose the fourth dropout conditional on the third dropout, contrary to information use in our data. Instead, the observed pattern is more in agreement with the signal averaging rules (models (6) due to Levin et al. (1996) and (7)). Both signal averaging rules correctly predict that the

²²Conditional on using information summarized in the previous dropouts, earlier bids do not add additional explanatory power. There is indeed a correlation to earlier bids, which is fully captured in the reaction to the current dropout. Repeating (3) and (4) without $d_{j-1,g,t}$ yields significant coefficients on $d_{j-2,g,t}$.

²³This analysis does not shed light on the possibility that the strong weight on the most recent dropout is due to correlation neglect (Enke and Zimmermann, 2019). With correlation neglect, information in early drop-outs is double-counted in later dropouts. In the Appendix, Table 16, we present regressions similar to the above, while excluding bidders' private information. We then predict residuals in this estimations, which capture bidders' private information (their signals and noise). We then regress later bids on all residuals. We find little evidence for strong correlation neglect, as especially residuals from late dropout orders most strongly explain variation in bids. This suggests that subjects understand that the most recent dropout contains information of the signals conveyed in the earlier dropouts.

²⁴We verified that our findings are not driven by the linear impact of information, by repeating (4) and (8) with the additional regressors $(s_{i,t})^2$ and $(d_{3,g,t})^2$. Both are not significant in either model.

²⁵Applying OLS to simulated bids also recovers the coefficients presented in Table 3.

last dropout is a sufficient statistic for all previously revealed information, as this bid summarizes all previously revealed information. Qualitatively, the Bayesian signal averaging rule (model (7)) performs particularly well, as it approximates the relative weight on last dropout compared to the own signal more closely than in (6). A further pattern in favor of Bayesian signal averaging is that bidders do not ignore the prior. In the AV, which offers the cleanest view on whether subjects use the prior, bids are anchored towards the mean common value. Bidders who receive a signal above 100 bid on average 72.4% of their signal, while bidders with a signal of at most 100 bid on average 117.4% of their signal.

Still, the bids predicted by the Bayesian signal averaging rule do differ significantly from observed behavior. The intercepts across all dropout orders are quite large and lead to the observed overbidding.²⁶ As later bids are incorporating revealed information, also constant overbidding early on carries over to later bids, which then determine revenue.

One remaining question is whether observed early dropouts are informative for subsequent bidders, and in how far bidders could use these bids to improve their estimates of the common value. In Nash equilibrium, all available information should be used when best responding, see model (5). However, early bids differ systematically from Nash equilibrium bids, and are potentially less informative of the common value than they are in Nash equilibrium. The informativeness of early bids should determine how later bids should respond to early bids. We proceed by using two types of analyses: studying (i) how informative bids are of the value and (ii) how information is used in an empirical best reply.

In estimation (8) we provide an analysis of the informational content of observed bids. We regress the common value on the information available to the bidder dropping out fourth. This analysis studies how the information available to the bidder determining the price is predictive of the common value, which at the end of each round is revealed to the subjects. Thus, model (8) provides a benchmark of what information is useful to bidders when attempting to predict the value using a linear rule.²⁷ In model (8), we observe that it is sufficient for bidders to attach positive weights only to the third dropout and own signal to predict the common value. This implies that early bids are not useful to predict the common value, which in fact our subjects appear to incorporate by disregarding this information. However, the relative weights attached to the third dropout

²⁶In fact, we can reject the coefficient restrictions implied by (5) to (7) in F-tests based on the estimated equation (4), with p -values=.000.

²⁷Note that the positive coefficient on t is a mechanical effect of all bids decreasing in t (see (1) to (4)), as $V_{g,t}$ is in expectation constant over time.

relative to the own signal differ strongly from the rule predicting the value, as bidders appear to react too much to the third dropout given the informational content of these bids.

In (9), we study how information would be weighted in an empirical best response. In this, we assume that the two bidders that remain in the auction longest bid the expected value of the item for sale, conditional on the other remaining bidder holding an equally high signal as the own signal, and incorporating information revealed in the previous dropouts. To infer signals from early dropouts, we use linear regressions in which we regress signals on observed bids, round, session fixed effects and signals predicted from earlier bids if available.²⁸ We then calculate the conditional expected value using the result by DeGroot (2005), as for Nash equilibrium bids for the bidder dropping out fourth. This establishes how close bidders could have estimated the value in our experiment using linear rules and the information on the value and signal distributions we provided. This is a best response under the assumptions that the two remaining bidders use the same procedure and that the inferred signals from previous dropouts are distributed as the true signals are (that is, conditional on the value they are *i.i.d.*, $\mathcal{N}(0, 35)$). We then regress the obtained empirical best response on the same set of observables for the second-highest bidder.

Consistent with the findings of model (8), (9) shows that early bids optimally receive little weight in an empirical best response. Due to early bidding being less informative than in Nash equilibrium, the optimal weights are below the weights on observed bids in model (5). However, even if the estimated coefficients are small, they are significant and positive. Again similar to (8), (9) shows that bidders do not rely sufficiently strongly on their own signal when bidding, and disregard valuable information in bidding.²⁹

We conclude that subjects' bidding is consistent with them paying attention to what happens in the JEA, and that how their bidding weighs information in the own signal relative to the observed dropout is qualitatively in line with Bayesian signal averaging. Still, our data does not accord with the prediction of the Bayesian signal averaging model that lower revenue will result in the JEA than in the AV. In the next section we address this puzzle.

²⁸We reproduce these estimations in the Appendix, Table 13.

²⁹Note that R^2 is mechanically high in this regression, as the conditional expected value is calculated based on these early dropouts. The R^2 does not account for the noise when inferring signals from bids.

6.3 Explaining heterogeneity in bidding

Bidding behavior in the JEA is quite heterogeneous, and especially so at early dropouts – in Table 3, we see that the R^2 increases in dropout orders. Additionally, especially at early dropout order subject-level fixed effects add significant additional explanatory power. This suggests that individual-specific characteristics are especially important at early stages of the auctions.

To shed light on whether there are systematic patterns in this heterogeneity in bidding behavior, we elicited subjects' social value orientation and their tendency for imitation at the end of the experiment for the last 13 sessions. For the imitation measurement, subject could choose to sample non-informative social information of prior participants instead of obtaining an informative signal. This behavior is consistent with a desire to imitate others. Participants that chose to reveal uninformative choices are classified as an imitator, which applies to 26.9% of our participants.³⁰ Social value orientation is measured as an angle, where 0° correspond to a dictator keeping all to herself, 45° giving an equal amount to recipient and herself and 90° giving everything to the recipient. We find an average SVO of 21.13° , with a standard deviation of 20.00° .

To investigate whether these measures correlate with heterogeneity in bidding behavior we exploit that the estimations in Table 3 provide us with estimates of bidder fixed effects. In this context, the bidder fixed effect captures bidder-specific level shifts of bids, holding the use of information constant across bidders.

Per participant, we average the fixed effects of the first and second dropouts as well as the fixed effects from the third and fourth dropout. We then combine data from the AV and the JEA to study whether there are systematic auction-specific effects. To do so, we regress the averaged fixed effects on subjects' social value orientation and imitation proneness, both interacted with a treatment dummy. Table 4 presents OLS estimates.³¹

The bidder characteristics we elicit appear to explain some of the heterogeneity in bidding we observe. First, subjects in the JEA delay their early dropouts, compared to the AV. For these early dropouts, bidder fixed effects are decreasing in subjects' social value orientation only for the open auctions. That is, more pro-social bidders bid higher on average in the AV, but more pro-social bidders bid on

³⁰In a similar setting, Goeree and Yariv (2015) find that 34% of subjects chose such information.

³¹In the Appendix, Table 17, we show that results are robust to using WLS. This addresses concerns that some fixed effects might be estimated more noisily than others. These observations receive less weight in variance-weighted WLS.

Table 4: Bidder fixed effects and their characteristics

	Average bidder fixed effect			
	d_1 & d_2		d_3 & d_4	
JEA	8.101**	(2.847)	3.595	(2.945)
SVO	0.125**	(0.043)	0.005	(0.115)
JEA \times SVO	-0.326**	(0.141)	0.021	(0.135)
Imitator	5.699***	(1.415)	6.528*	(2.985)
JEA \times Imitator	-0.486	(3.794)	-4.953	(3.016)
Constant	-1.876	(1.835)	-4.674**	(1.605)
Observations	90		90	
Adjusted R^2	0.012		0.036	
Estimation	OLS		OLS	

Notes: Average fixed effects from regressing bids on available information for first and second vs. third and fourth dropout; pooling data from the AV and the JEA. SVO is a subject's social value orientation, in degrees. Imitator is a dummy variable equal one if a subject chose to retrieve social information when this contains no valuable information on the true state. Standard errors in parentheses, clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

average lower in the JEA.³² This effect is consistent with the intuition that spiteful bidders may stay longer in the JEA in order to deceive their opponents about their signal: if other subjects observe a very high dropout, they may mistakenly infer that this dropout is associated with a particularly high signal.

That an effect in this direction occurs only in the JEA is not too surprising. In the AV, bidders cannot observe whether other subjects have already exited the auction, thus these exits cannot influence subsequent bidding. Additionally, overbidding for the early dropouts in the JEA is (almost) costless because such bidders can avoid winning when one of the other bidders drops out by immediately dropping out as well. Furthermore, there is no significant difference in how imitators behave between auction formats in early bidding, in both treatments they are willing to bid higher than non-imitators. The fact that there is no interaction effect for imitators in the JEA hints at the possibility that this measure may not only capture a tendency to imitate but also general overbidding caused by confusion.³³ Point estimates with experienced bidders are similar, see Table 11 in the Appendix. The fact that some of the estimates are no longer significantly different from 0, notably the interaction effect of SVO in the JEA, may be due to

³²Note that in this task, inequality averse participants are classified as pro-social. Therefore, bidding higher initially in the AV can be consistent with bidders trying to minimize payoff inequality, which might arise if an opponent wins at a low price.

³³There are also situational factors that affect the extent of overbidding. For instance, [Levin et al. \(1996\)](#) and [Goeree and Offerman \(2002\)](#) find that subjects' overbidding enhances with the variance of the noise term in the signals.

a lack of power.

The observed impact of these two behavioral forces on bidding levels can have a substantial impact on revenue. To illustrate this effect, we predict revenue using the information use found in Table 3, while incorporating predicted bidder fixed effects obtained by the model in Table 4, by systematically varying SVO and imitation measures. For simplicity, we predict fixed effects assuming a homogeneous SVO- and imitation-measure across all bidders. Then, we iteratively predict bids using the results found in Table 3, using the signal draws from our experiment. In the JEA, revenue is predicted to vary in these underlying characteristics as captured by the following equation:

$$R_{JEA} = 105.29 - 0.15 \times \text{SVO} + 5.43 \times \text{Imitator}$$

For interpretation, the interquartile range for SVO ranges from .48° to 42.50°, and ranges from a minimum of -18.47° to a maximum of 57.32°. For Imitator, both ranges correspond to moving from 0 to 1. For example, moving bidders from homogeneously pro-social at the third quartile to homogeneously more selfish at the first quartile leads to revenue gains of 6.3 points.

For the AV, the effect of spiteful bidders is negligible. This is the case as only the fixed effects at the fourth dropout order have a revenue impact, as earlier dropouts are unobservable and do not affect later bids. Imitators affect revenue similarly across the two formats. In particular, revenue in the AV is predicted to vary in these characteristics by:

$$R_{AV} = 98.67 + 0.01 \times \text{SVO} + 6.53 \times \text{Imitator}$$

We conclude that the (approximate) revenue equivalence observed between the JEA and the AV results from two opposing behavioral forces. On the one hand, processing information in the spirit of Bayesian signal averaging allows subjects to avoid the winner’s curse in the JEA. On the other hand, spiteful bidding in the JEA can enhance revenue.³⁴

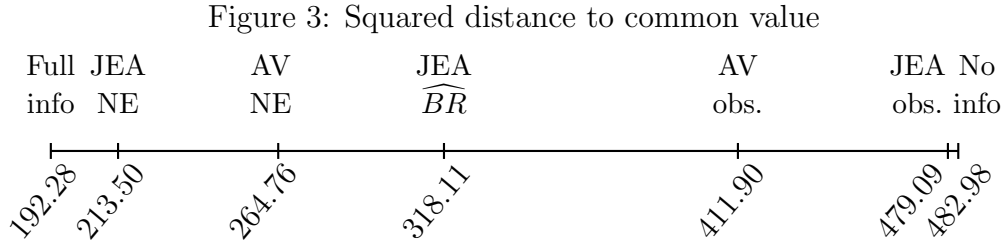
³⁴Another candidate to explain deviations from risk neutral Nash bidding is risk aversion. Because all auctions use the second-price rule and there is uncertainty about the value, risk aversion will have a downward pressure on Nash equilibrium bids (see also Levin et al. (1996)). Given that observed bids tend to be higher than risk neutral Nash equilibrium bids, we think that risk aversion is a less important force in our experiment. Similarly, the heterogeneous behavior of early dropouts is not only incompatible with the symmetric equilibrium in Milgrom and Weber (1982), but also with the asymmetric equilibria in open auctions identified by Bikhchandani and Riley (1991). In addition, the asymmetric equilibria predict lower revenues in the JEA, while we observe revenue in excess of the symmetric Nash equilibrium.

6.4 Information aggregation

In this Section, we investigate the extent to which bidders aggregate information in the different formats. The measure of information aggregation is the squared distance between the price and the common value, as explained in Section 4.

We first present a comparison between the JEA and the AV, the two auctions that differ only in the information on previous dropouts. Both rational and behavioral benchmarks predict that additional information improves bidders' precision in estimating the value. This prediction, however, is not borne out in our data. Figure 3 plots the distance between price and value that is actually observed in the data. For a comparison, it also includes Nash equilibrium predictions.

As it turns out, the theoretically predicted ranking is reversed in our data. The observed squared distance in the AV is 411.9, and *increases* to 479.1 when *more* information is available in the JEA. This difference is statistically significant (p -value=0.028, MWU, 10 observations per treatment). Actually, the JEA aggregates almost no information. The observed squared distance of the JEA is not statistically different from the No Information benchmark, where the price is set equal to the prior mean of the common value, ignoring all information contained in signals.³⁵

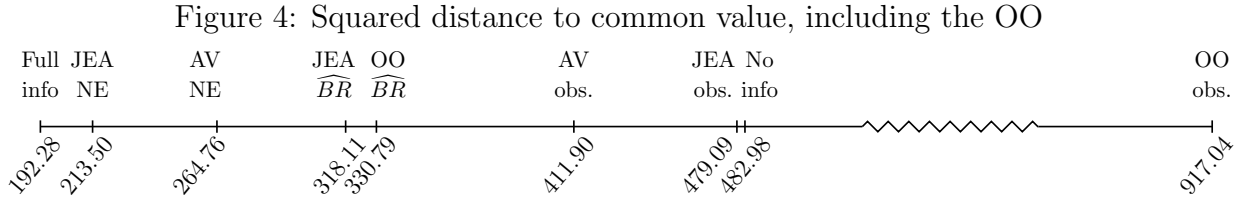


There can be two reasons why information aggregation fails in open ascending auctions: i) there is not sufficient informational content in observable bids (*information revelation*) (ii) bidders do not process the available information as a rational bidder would (*information processing*). To isolate the two forces, we use an empirical best response \widehat{BR} as described in Section 6.2, given observed bidding behavior of early dropouts. Note that \widehat{BR} is a statistic that separates between information processing and revelation. It represents the level at which two re-

³⁵We verified that the same ordering in our results on information aggregation is observed when using the squared distance to the Full information benchmark as a measure, instead of the squared distance to the common value. The latter does not directly control for variance in signals conditional on the common value. In our analysis, this is captured by the distance to the common value measured in the Full information benchmark.

maintaining bidders best respond to each other, when they incorporate information available in the experiment. The gap between the observed level of information aggregation (JEA obs.) and the maximal level of aggregation achievable given the available information (\widehat{BR}) serves as our measure of the failure of information processing. Failure in information revelation is measured by the distance between \widehat{BR} and JEA NE, as in Nash equilibrium signals from earlier dropouts can be inferred perfectly. From inspecting the segment, it is apparent that both forces play a role: Information in the JEA is dissipated by noisy early dropouts and further processed in a sub-optimal way.

The higher revenue that we observe in the OO is not caused by a higher degree of information aggregation in that format. To the contrary, in the OO overbidding is so severe that the price is a highly inaccurate predictor of the common value, resulting in a very imprecise measure of information aggregation, with a squared distance of 917.0. If bidders had simply ignored their private signal and the bidding of others, and bid the prior mean value according to the no-information benchmark, this distance would shrink to 483.0. Figure 4 presents the information aggregation benchmarks of the OO in comparison to the other auction formats.



This lack of information aggregation cannot be attributed to information in bids being obfuscated. The same decomposition as performed for the JEA shows that the second-highest bidder in the OO would be able to predict the common value relatively well if they attempted to bid the conditional expected value as in the JEA, by incorporating the own signal and the maximal bids of the three non-winners. This is a conservative measure of how much information is potentially available in the OO, because it ignores other, possibly informative, observables such as the time elapsed between bids, the size of the jump bids, or the number of returning bidders.

6.5 Bidding in Oral Outcry auctions

While information revelation does not lead to higher revenue, we have previously seen that revenue is higher in the OO than in the other two formats. Also, infor-

mation aggregation in this format fails.

The OO differs from the two clock-formats in how bids can be submitted. In both the AV and the JEA, the price rises at an exogenously set pace and bidders can only decide whether to leave or remain at every price. In the OO, bidders can submit their own bids. In the following, we discuss two ways in which this change matters: it may trigger a quasi-endowment effect in bidders, as well as allow for non-incremental jump bidding.

During an Oral Outcry auction, a standing bidder is identified, who is the highest bidder at that moment. The previous literature has established that this can induce a so-called auction fever (Heyman et al., 2004; Ehrhart et al., 2015). A standing bidder may get used to the feeling of winning the good and become prepared to bid higher than she originally intended. If that happens, auction fever triggers a quasi-endowment effect.

Auction fever is in agreement with the fact that we observe relatively many extreme auction revenues in the OO compared to the other two formats, beyond the average revenue already being significantly higher in the OO. For example, only 1.3% of all common values are in the right hand tail of the common value distribution, at values above 150. In both the AV and the JEA, less than 1% of auctions end up at revenues above 150. In the OO in turn, 7.3% of auctions conclude at prices above 150, suggesting that especially this format triggers strong mispricing.

To evaluate the impact of auction fever, we use bidder's exogenously measured inclination to succumb to the endowment effect, and perform a median split based on this measure.³⁶ There are two main effects: (i) bidders do not systematically differ in how often they win auctions (MWU-test, p -value=.773), thus bidding behavior appears similar at first; (ii) whenever they win an auction, bidders with stronger endowment effects generate higher losses than their peers, as their total profits are significantly different (MWU-test, p -value=.083)³⁷ thus when becoming active and winning an auction, bidders with strong endowment effects lose more money. This evidence provides clear support for the conjecture that the OO activates auction fever among people who suffer from the endowment effect.

³⁶We normalize both measures to mean 0, variance 1, then take the average response as a measure of the endowment effect. We compare matching group averages of those bidders with above and below median endowment effects, yielding 8 observations (4 matching groups, one observation above and below the median each).

³⁷This analysis is robust to (i) performing a median split based on the first principal component obtained from the two measures of the endowment effect as well as (ii) regressing the number of auctions won and winners' profits on their endowment effect, the latter analysis is reproduced in the Appendix, Table 18.

A second important feature of the OO is that bidders can submit non-incremental jump bids. Theoretical analyses of jump bidding predict that winners in auctions make higher profits when jump bidding is possible (Avery, 1998; Ettinger and Michelucci, 2016). Naturally, behavioral factors like impatience may also motivate jump bidding. In this case, jump bidding may decrease winners' profits. Note that within our auctions and due to the second-price rule in setting the current price, jump bids are only revealed if at least one other bidder continues to bid. While submitting additional bids, other bidders learn that the jump bidder has entered an aggressive jump bid, as the jump bidder continues to be the standing bidder. The level of the jump bid is revealed at the moment that some other bidder enters a bid higher than the jump bid. This feature captures how jump bidding in popular auction formats occurs. As such, we expect weaker effects of jump bidding than in first-price formats, where the level of a jump bid is revealed immediately. In our analysis, we will show that even this subtle effect of jump bidding matters for outcomes.

As a measure of jump bidding we use the increment of a new bid above the current price, the second highest bid submitted in previous bidding rounds, at the moment the new bid was submitted. By the rules of the auction, jump bids vary between 1 point, which is the minimum increment, and 200 points, if the maximum possible bid was submitted straight at the start of the auction. Often, the same bidder submits multiple bids. We denote the sum of all jump bids for one bidder across one auction as the total jump bid of this bidder. In estimations, we also frequently use the jump bids submitted at the start of an auction, when the price stands at 0, and denote these as the starting jump bids. As these bids are submitted when no information is revealed yet, they do not suffer from the same risk of endogeneity concerns as other jump bids that are submitted later in the auction.

We observe extensive jump bidding: 21.6% of bids exceed the current price by at least 20 points, and 11.2% by at least 50 points. Jump bidding is most prevalent at the start of an auction, where 81.7% of entered bids are at least 20 points, and 60.4% are at least 50 points high. Jump bidding also gains in popularity over time: in the first 15 rounds, the average jump bid at the start of an auction is 53.8, this increases to an average of 61.6 in the last 15 rounds.³⁸

³⁸In the first six sessions, the bidding rounds at which a bid was submitted was not saved correctly due to a programming mistake. We reconstructed this data by the time stamp at which bids were submitted. In 10.7% of the bids in these sessions, this classification is potentially ambiguous, we assumed that bids were submitted in a later bidding round in these cases, which leads to potentially fewer bids being considered for our type of analysis. The results we

In Table 5, we show regression results on the use and effect of jump bids. The main regressor of interest is the total jump bid, the sum of all bid increments by each bidder in an auction. However, these bids are likely endogenous. Therefore, in this regression, we use the jump bids submitted at the start of an auction to instrument for the total jump bid (using 2SLS). That is, in a first stage, we predict the total jump bid of each bidder using the starting jump bid and the other used variables, such as the signal $s_{i,t}$. In the second stage, we regress our dependent variables of interest on this predicted total jump bid and some other variables. This provides a clean identification of the effect of jump bids. However, we are still constrained by the set of bidders who do submit a bid at the start of each auction, as we cannot obtain instruments if this is not the case.³⁹

Table 5: Effect of jump bids in the OO

	(1)	(2)	(3)	(4)
	Jump bid	Pr(win)	Mean earnings	Winners' profits
Jump bid (IV)		0.207*** (0.046)	-0.034** (0.014)	-0.006 (0.047)
$s_{i,t}$	0.322*** (0.021)	0.175*** (0.038)	-0.020* (0.011)	-0.043 (0.053)
t	0.453*** (0.132)		0.170*** (0.047)	0.913*** (0.177)
$V_{g,t}$			0.134*** (0.016)	0.557*** (0.063)
Constant	18.251*** (4.808)	-11.298*** (3.061)	-14.117*** (3.217)	-76.641*** (11.844)
Observations	1433	1433	1433	312
Estimation	OLS	2SLS	2SLS	2SLS

Notes: Jump bid is the increment of a bid beyond the current price at the moment the bid was submitted. In (1), we regress the jump bid at a price of 0 on bidders' signals. In (2) to (4), we use 2SLS, where we instrument the total jump bid per bidder with the jump bid at a price of 0. (2) is the ex-post probability of winning, which is a dummy equal to one if a bidder wins the auction, 0 otherwise. Mean earnings are a participants' average earning across all auctions, winners' profits are the earnings for the auctions which a participant won. $s_{i,t}$ is the submitting bidder's signal in round t . $V_{g,t}$ represents the common value. Standard errors in parentheses, clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (1) presents results of regressing these jump bids on bidders' information. As predicted by theoretical models, bidders with higher signals submit

present are robust to instead assuming that these bids were submitted simultaneously, or randomizing this classification. Also, only using data from the last four sessions, where this error was corrected, yields similar results.

³⁹We can obtain instruments for 1433 observations, out of 2687 total observations.

higher jump bids. The size of the jump bid is significantly increasing over time.⁴⁰

Table 5 also presents an analysis of the effects of jump bids. Across all IV estimations, the first stage is highly significant, so we do have relevant instruments, exceeding the rule-of-thumb of an F-statistic of 10 (Staiger and Stock, 1997): early jump bids are predictive of the overall jump bidding behavior.⁴¹

In (2), we show that within the set of the bidders who submit a bid at the start of the auction, the probability to win an auction increases in the jump bid, controlling for the signal of this bidder. The dependent variable is a dummy equal to one when a bidder wins the auction, 0 otherwise. Therefore, within the set of bidders who decide to become active immediately at the start, the bidder who enters the largest jump bid is most likely to win this auction. This is consistent with the signaling motive in the theoretical literature.

Models (3) and (4) then study how profits are affected by the size of the jump bid. (3) again conditions on the set of bidders who immediately enter a bid. Profits are significantly decreasing in the size of the jump. This is the opposite of the effect predicted by theory.

However, winners on average lose money in the OO and, by submitting a jump bid, participants select into this group of winners making a loss. To study this further, (4) restricts the analysis to bidders who end up winning the auction and simultaneously submit a bid at the start of the auction. Within this group of bidders, the size of the jump bid does not decrease profits further.

Results for experienced bidders are similar, see Table 12 in the Appendix. In later rounds, jump bidding has a more negative effect on earnings, and the effect of jump bids on Winner’s profits (model (4)) is also significant, suggesting that jump bidding continues to be a disadvantageous strategy with more experience, while jump bidding is in fact used more extensively later on.

7 Conclusion

In this paper, we study some salient factors that can contribute to the popularity of open ascending auctions. In particular, we assess the roles that endogenous information aggregation and behavioral biases play in explaining their prevalence. In a common value setting, we compare two clock auctions, the ascending Vickrey

⁴⁰In the last 4 sessions, we elicited how much participants agreed with several motives for jump bidding in the questionnaire, see Appendix Section C.1 for details. If we include those in (1) as controls, the only statement that correlates significantly with the size of the jump bid is “I tried to deter other bidders from bidding by entering a bid much higher than the current price.”

⁴¹F-statistics are 1050.95 for (2), 723.10 for (3) and 3033.74 for (4), with all p -values=.0000.

auction (AV) and the Japanese-English auction (JEA), which differ in irrevocable exits of bidders being observable only in the latter. We also study the Oral Outcry auction (OO), an auction format modeled to approximate popular designs, in which bidders choose how much information they want to reveal through bids.

In agreement with their popularity, we find that the OO is most successful in raising revenue. The JEA raises similar revenue as the AV, in contradiction to both the rational benchmark which predicts higher revenue for the JEA and some behavioral models that predict higher revenue for the AV. We find that information aggregation fails in the JEA. Bidding in the JEA reflects a worse estimate of the common value than in the AV.

It is not the case that bidders do not pay attention to early exits in the JEA. To the contrary, bids correlate strongly with the most recent dropout they observe.⁴² This pattern deviates from what would be observed either with Nash bidders, what is justified based solely on the informational content of early dropouts or with an empirical best response. The relative weight of how bidders incorporate information is best captured by a Bayesian signal averaging heuristic. However, all models incorporating public information underestimate bid levels and bidders in the JEA do not use public information sufficiently to temper the winner’s curse, as predicted by signal averaging models.

At the same time, bidding behavior conveys less information than the theoretical benchmark. The information reflected in early dropouts of the JEA is partly obfuscated by substantial heterogeneity in the bidding of early leavers. We find two forces that explain some of this heterogeneity. In the JEA, spiteful bidder stay too long in the auction early on. Such spiteful bidding by early leavers neutralizes the revenue diminishing force of the Bayesian signal averaging heuristic. Our support for a spiteful motive resonates with some empirical findings in other auction environments (Andreoni et al. (2007), Bartling and Netzer (2016)).

In the OO, bidders choose how much information to reveal through their bids. Overall, bids in the OO convey as much information as those in the JEA. However, in the OO-format the available information is least well processed, and the price paid by the winner approximates the common value worst among all three formats.

Instead, the OO activates some behavioral biases that enhance revenue. Bidders who suffer from endowment effects lose more money in these auctions. When they become the provisional winner, auction fever strikes and they become willing

⁴²Note that Hoelzl and Rustichini (2005) find that people are underconfident in complicated tasks. Their result agrees with our finding that bidders pay relatively much weight to what others do in the strategically complicated common value setup.

to submit higher bids than otherwise expected. In addition, the OO encourages bidders to submit jump bids. In contrast to the theoretical literature, jump bids do not enhance winners' expected profits. Jump bidders are more likely to win the auction, but they tend to lose money doing so.

Oral Outcry auctions may be popular not because they allow bidders to aggregate information. Instead, a more important rationale for using Oral Outcry auctions may be that they activate revenue enhancing behavioral biases.

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A Appendix

In this Appendix, we start with an analysis of information effects on eBay. Then, we discuss revenue predictions for different parameterizations, and we present behavioral models.

A.1 Information usage on eBay

eBay gives bidders access to a detailed bidding history during an auction. To investigate the effects of information use on eBay, we collected data from eBay-auctions between August 8 and September 27, 2019. We chose one of the most frequently auctioned cellphones in that moment, the Apple iPhone X, 64GB, with a total of 1194 phones. These phones vary considerably in the condition they are sold, with buyers potentially making inference on the phone’s value for example based on pictures, descriptions, or the sellers’ reviews. Crucially, the interested bidders can study others’ bids, which may allow them to learn about a specific phone’s value.

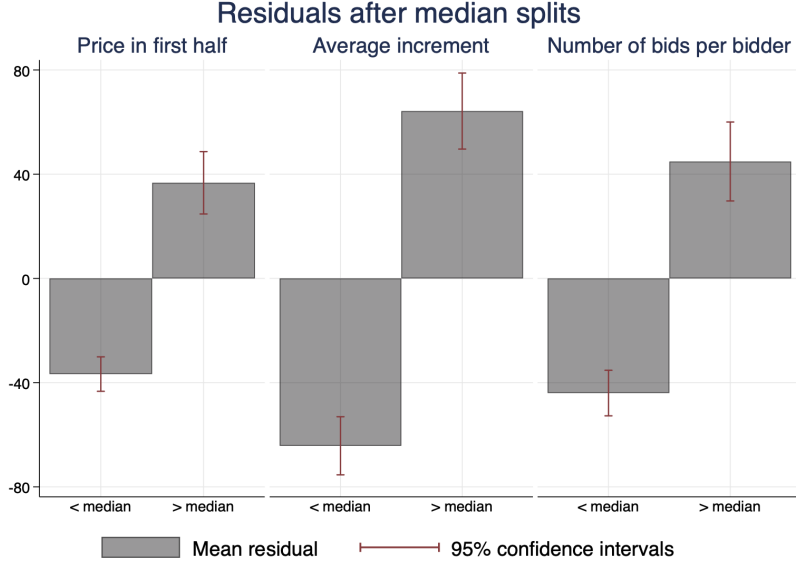
To explore this endogenous learning, we perform median splits of the data on a number of dimensions which might convey information during the auction, such as the interim price, the number of bids per bidder and the average increments between consecutive bids. We then study if median splits along these variables explain variation in the final price. Before performing the median splits, we regress the final price on a number of observable characteristics, such as the (exogenously set) length of the auction, the reserve price, the number of bids and the number of bidders, as well as the review count of the seller. By extracting the residuals obtained from these regressions, we factor out all variation that can be explained by these observable exogenous characteristics.⁴³

In Figure 5, we plot the average residual for cellphones above and below the median for each of the three different splits of the data. First, we split the auctions based on the price of the cellphone when half of the total length of the auction elapsed. Second, we perform a split based on the average increment per bidder (given by the price at the end less the reserve price, divided by the number of bids submitted). This captures the degree of jump bidding observed. Third, we split on the number of bids per bidder.

We observe that the average residuals of the iPhones are different depending on which half of the data they are categorized in. The effects are also quite sizable,

⁴³The described pattern is also found when directly comparing prices across the same median splits.

Figure 5: Residuals obtained from regressions of final price



as the average price of the phones is \$425.8, standard deviation of \$175.8. This implies that there is systematic variation in the prices of these phones which cannot be explained by the observable exogenous characteristics. Instead, this residual variation can be explained by the categories we perform the median split by, and these variables may capture information generated endogenously in the auction. This indicates that information revelation might matter.

Crucially, this type of observational data cannot be used to establish unambiguously that information revelation is taking place and what effect revealing information has. First of all, the direction of causality is not clear (e.g., are expensive phones attracting many bids, or do many bids increase the price?). More importantly, we cannot evaluate what information is processed without observing bidders' information sets and the underlying value of the good to be sold. Also, we are unable to determine the impact of information without providing a control condition where no information is being revealed. However, this is possible in our laboratory experiment.

A.2 Revenue predictions for different parameterizations

In the choice of parameterizing the mean and variances of the values and signals for this experiment, we simulated revenues of the AV and the JEA to generate predictions of the symmetric Nash equilibrium. In Table 6, we report results of these simulations. For each parameterization, we draw 50,000 sets of signals

according to the procedures of the draws for the experiment, then calculate average revenues based on all simulated bids. In Table 6, R_{AV} are revenues in the AV, R_{JEA} are revenues in the JEA. We simulate different parameterizations, for the full set of parameters $(\mu, \sigma_V, \sigma_\epsilon)$, which is the mean μ and standard deviation σ_V of the value distribution as well as the standard deviation σ_ϵ of the error distribution. Within each parameterization, we give mean revenues in the first row, and the standard deviation of the revenue in the second row. From the Table, it is clear that revenue differences of the Nash equilibrium are quite small across specifications. Theoretical revenue differences for uniformly distributed values and errors are similarly low, the case studied by the previous literature.

Table 6: Revenue Nash predictions with varying parameters

$(\mu, \sigma_V, \sigma_\epsilon)$		R_{AV}	R_{JEA}
(50, 10, 12)	Mean	48.3555	48.7510
	Standard deviation	(8.3056)	(8.6844)
(100, 10, 12)	Mean	98.3877	98.7540
	Standard deviation	(8.4207)	(8.8667)
(100, 10, 30)	Mean	98.3874	98.5852
	Standard deviation	(5.3808)	(6.0436)
(100, 20, 20)	Mean	96.9314	97.6790
	Standard deviation	(17.6035)	(18.2750)
(100, 20, 30)	Mean	96.5708	97.4156
	Standard deviation	(15.1637)	(6.0436)
(100, 20, 40)	Mean	96.1720	97.2063
	Standard deviation	(12.7600)	(12.4809)
(100, 30, 20)	Mean	96.6016	97.5939
	Standard deviation	(26.8225)	(27.2350)
(100, 30, 30)	Mean	95.4797	96.9314
	Standard deviation	(23.5650)	(24.1363)
(100, 40, 40)	Mean	92.9095	95.5161
	Standard deviation	(26.4453)	(26.4859)
(200, 40, 40)	Mean	194.1535	195.6345
	Standard deviation	(35.1111)	(36.3651)

Additionally, we calculated revenue differences for varying numbers of bidders. In Table 7, for the parameterization used in this experiment, $(\mu, \sigma_V, \sigma_\epsilon) = (100, 25, 35)$, we state Nash equilibrium revenue differences for different numbers of bidders. Evidently, theoretical revenue differences between treatments are not driven by the size of our auctions.

Table 7: Revenue predictions varying number of bidders, $(\mu, \sigma_V, \sigma_\epsilon) = (100, 25, 35)$

Number of bidders		R_{AV}	R_{JEA}
3	Mean	93.4861	94.2020
	SD	(18.0011)	(18.2828)
5	Mean	95.6073	96.9290
	SD	(18.2036)	(18.9653)
7	Mean	96.1953	97.7570
	SD	(18.1058)	(19.0956)
9	Mean	96.6706	98.4264
	SD	(17.7684)	(18.8915)
11	Mean	96.6956	98.5875
	SD	(17.6533)	(18.7593)

A.3 Naïve models

In this section we discuss some behavioral models that have been discussed in the literature, to explain observed behavior in the AV and the JEA. In the AV, there are two principal behavioral models which might capture bidding behavior. First is the “bid signal”-heuristic, according to which bidders might just enter a bid equal to their own signal:

$$b(S_i) = S_i$$

In expectation, this will result in overbidding of the winning bidder, as the bidder neither includes information on the distribution of signals and values nor considers the informativeness of winning.

Second, somewhat more sophisticated bidders will incorporate information about the prior distribution of the value. In the “Bayesian bid signal”-heuristic, bidders still suffer from the Winner’s curse, but bid the expected value of the good for sale, conditional on one’s signal, as in Goeree and Offerman (2003b).⁴⁴

$$b(S_i) = \mathbb{E}[V|S_i] = S_i - \mathbb{E}[\epsilon_i|S_i]$$

To explain behavior in the JEA, Levin et al. (1996) propose a “signal averaging rule”, according to which bidders bid an equally weighted average of their own signal and the signals of their fellow bidders, revealed from the previous dropouts. This rule incorporates revealed information in a natural way.

⁴⁴Within the setup of our experiment, we can use that $\epsilon_i|S_i \sim \mathcal{N}\left(\frac{\sigma_\epsilon^2(S_i - \mu)}{\sigma_\epsilon^2 + \sigma_V^2}, \frac{\sigma_\epsilon^2 \sigma_V^2}{\sigma_\epsilon^2 + \sigma_V^2}\right)$. As derived in Goeree and Offerman (2003b): $b(S_i) = \frac{\sigma_V^2 S_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$

Close to the bid-signal heuristic is the “symmetric signal averaging rule”, introduced by [Levin et al. \(1996\)](#). Here, all bidders assume that all other bidders follow this rule as well. After k bidders dropped out, with the vector of revealed signals being \mathbf{S}_j , this implies the following bid:

$$b_k(S_i, \mathbf{S}_j) = \frac{1}{k+1}S_i + \frac{1}{k+1} \sum_{j=1}^k S_j$$

This formulation can be rewritten to only depend on the last dropout price, for the vector of previous dropout prices \mathbf{p}_k , p_j being the j -th observed dropout:

$$b_k(S_i, \mathbf{p}_k) = S_i + \frac{k}{k+1}p_k$$

A variant of this rule is the “asymmetric signal averaging rule”, according to which bidders assume that other dropouts are based on the heuristic of bidding equal to signal. This would enable bidders to more easily include others’ information. Additionally, it appears to be an intuitive rule given the information salient in the auction process. If bidders follow the asymmetric signal averaging rule, with p_j being the j -th dropout, bids are given by:

$$b_k(S_i, \mathbf{p}_k) = \frac{1}{k+1}S_i + \frac{1}{k+1} \sum_{j=1}^k p_j$$

Similar to the “Bayesian bid signal” heuristic, signal averaging rules can also incorporate information about the prior. According to the “Bayesian signal averaging rule”, bidders apply Bayes rule in combination with the symmetric signal averaging rule. In this case, after k observed dropouts, bidder i calculates the average of available signals $\bar{S} = \frac{1}{k+1}S_i + \frac{1}{k+1} \sum_{j=1}^k S_j$:

$$b(\bar{S}) = \frac{\sigma_V^2 \bar{S} + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$$

While it is unlikely that a bidder that is sophisticated enough to apply Bayes rule correctly would rely on a signal averaging rule, Bayesian signal averaging is most of all useful in anchoring bidding to the prior, compared to standard signal averaging. Even if Bayes rule in itself is too sophisticated, it is also unlikely that bidders rely purely on averaging available signals and fully ignoring all information on the prior distribution of values.

B Online Appendix to “Why are open ascending auctions popular?”

The remaining Appendix is intended for online publication. We present cursed equilibrium for the JEA and show the results for a horse race between different models in the AV and the JEA. We also present some robustness checks of the analyses in the main paper.

B.1 Cursed equilibrium in the JEA

As shown by [Eyster and Rabin \(2005\)](#), the expected payoffs from winning in the χ -virtual common value auction is given by:

$$\pi(V, p) = (1 - \chi)V + \chi\mathbb{E}[V|X_i = S_i] - p$$

for price p , compared to winners’ payoff in Nash equilibrium of $\pi(V, p) = V - p$. We continue to analyze a game where χ is homogeneous across participants, as well as during the auction. This implies bidder’s cursedness is not affected by observing other’s bids. From [Milgrom and Weber \(1982\)](#), we know that a symmetric Bayes Nash equilibrium in the JEA is given by

$$\begin{aligned} b_k(S_i) = \mathbb{E}[V|X_i = S_i, Y_{(1)} = S_i, \dots, Y_{(5-k-1)} = S_i, p_1 = b_0(Y_{(4)}), \dots \\ \dots, p_k = b_{k-1}(Y_{(5-k)})] \end{aligned}$$

This conditional expected value in a χ -virtual game is equal to

$$\begin{aligned} \mathbb{E}\left[(1 - \chi)V + \chi\mathbb{E}[V|X_i = S_i] \middle| X_i = S_i, Y_{(1)} = S_i, \dots, Y_{(5-k-1)} = S_i, p_1 = b_0(Y_{(4)}), \dots \right. \\ \left. \dots, p_k = b_{k-1}(Y_{(5-k)})\right] \\ = (1 - \chi)\mathbb{E}[V|X_i = S_i, Y_{(1)} = S_i, \dots, Y_{(5-k-1)} = S_i, p_1 = b_0(Y_{(4)}), \dots, p_k = b_{k-1}(Y_{(5-k)})] \\ + \chi\mathbb{E}[V|X_i = S_i] \end{aligned}$$

As [Milgrom and Weber \(1982\)](#) have shown that $b_k(S_i)$ is a Nash equilibrium in the original game, the expression above is a symmetric cursed equilibrium in a χ -virtual game, for $\chi \in [0, 1]$.

To employ cursed equilibrium, we need to estimate the additional parameter χ . This also provides a measure of the cursedness of our subjects.

We estimate for the AV:

$$b(S_i) = \underbrace{\left(S_i - \frac{\int_{-\infty}^{\infty} \epsilon \phi_V(S_i - \epsilon) \phi_{\epsilon}^2(\epsilon) \Phi_{\epsilon}^3(\epsilon) d\epsilon}{\int_{-\infty}^{\infty} \phi_V(S_i - \epsilon) \phi_{\epsilon}^2(\epsilon) \Phi_{\epsilon}^3(\epsilon) d\epsilon} \right)}_{=x_1} + \underbrace{\chi \left(\frac{\sigma_{\epsilon}^2 S_i + \sigma_{\epsilon}^2 \mu}{\sigma_V^2 + \sigma_{\epsilon}^2} + \frac{\int_{-\infty}^{\infty} \epsilon \phi_V(S_i - \epsilon) \phi_{\epsilon}^2(\epsilon) \Phi_{\epsilon}^3(\epsilon) d\epsilon}{\int_{-\infty}^{\infty} \phi_V(S_i - \epsilon) \phi_{\epsilon}^2(\epsilon) \Phi_{\epsilon}^3(\epsilon) d\epsilon} \right)}_{=x_2}$$

We simulate all terms using bidders' signals and then regress bids using OLS:

$$b(S_i) = \beta_1 x_1 + \beta_2 x_2$$

In a constrained regression, we impose no constant and $\beta_1 = 1$. Then, $\beta_2 = \chi$. For the JEA, we proceed similarly. We first simulate Nash equilibrium bids, based on the inference of observed dropouts.⁴⁵ We also use OLS to estimate χ in the following equation:

$$b_k(S_i) = \underbrace{\frac{5\bar{S}\sigma_V^2 + \mu\sigma_{\epsilon}^2}{5\sigma_V^2 + \sigma_{\epsilon}^2}}_{=x_1} + \chi \underbrace{\left(\frac{\sigma_V^2 S_i + \sigma_{\epsilon}^2 \mu}{\sigma_V^2 + \sigma_{\epsilon}^2} - \frac{5\bar{S}\sigma_V^2 + \mu\sigma_{\epsilon}^2}{5\sigma_V^2 + \sigma_{\epsilon}^2} \right)}_{=x_2}$$

We regress dropout prices on x_1, x_2 :

$$b_k(S_i) = \beta_1 x_1 + \beta_2 x_2$$

Again using constrained regression with no constant and $\beta_1 = 1$, we obtain $\beta_2 = \chi$. In Table 8, we summarize the regression results. We estimate χ once for all pooled data and once for the fourth dropouts in (2) and (4), respectively.

The coefficient on x_2 is $\hat{\chi}$, which turns out to be low in our sample. Recall that $\chi = 0$ corresponds to Nash equilibrium bidding, thus our bidding behavior appears to be close to this benchmark judged by the cursedness of the participant pool.

⁴⁵Note that we do not use the theoretical, unobserved signals other bidders hold for simulations. These predictions differ from the Nash equilibrium predictions by not incorporating realized dropout prices, but these do require inferences bidders are not able to make given the observed dropouts in the laboratory.

Table 8: Estimating χ

	(1) AV	(2) AV, d_4	(3) JEA	(4) JEA, d_4
x_1	1.000 (.)	1.000 (.)	1.000 (.)	1.000 (.)
$x_2 = \hat{\chi}$	0.058 (0.058)	0.985*** (0.072)	-0.137** (0.059)	0.186*** (0.041)
Observations	2417	598	2453	599
Estimation	OLS	OLS	OLS	OLS

Notes: Standard errors in parentheses and clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Horse race between models

To understand how bidding behavior can be characterized, we analyze how well individual bids can be predicted by the available models. For each bid in each round and based on the available information, such as the signals and observed dropouts, we simulate all models described previously. Then, we calculate the distance between each of the bids and all theoretical predictions, using the squared difference. Denote $\delta_{i,b,k}$ the distance of bid b by bidder i , compared to model k . $d_{i,j,g,t}$ is the observed dropout price of bidder i in group g in round t ⁴⁶, dropping out at order j . $d_{i,j,g,t}^k$ is the theoretically predicted dropout price by model k for this bid. The distance $\delta_{i,b,k}$ is given by:

$$\delta_{i,b,k} = (d_{i,j,g,t} - d_{i,j,g,t}^k)^2$$

After calculating each of the distances for all bids and models, we can determine which model fits individual bids best. Then, we calculate the average distance of all models across all bids. In other words, as a measure of fit, we state the mean squared error in predicting bids for each model.

To allow for a comparison of the size of the error, we also provide a benchmark linear rule.⁴⁷ For this, we run regressions which use the identical available information as the models, which is the bidder's signal and dropouts in case they are observable. We then state the mean squared error of this prediction. By design, this minimizes this error within the class of linear models, which nests all models which are competing in this analysis.

In our analysis, we distinguish bids by dropout order. The first dropout order are all bidders who drop out first in an auction, and so forth. Note that the fourth

⁴⁶Here, we only consider bidders who actively choose to drop out.

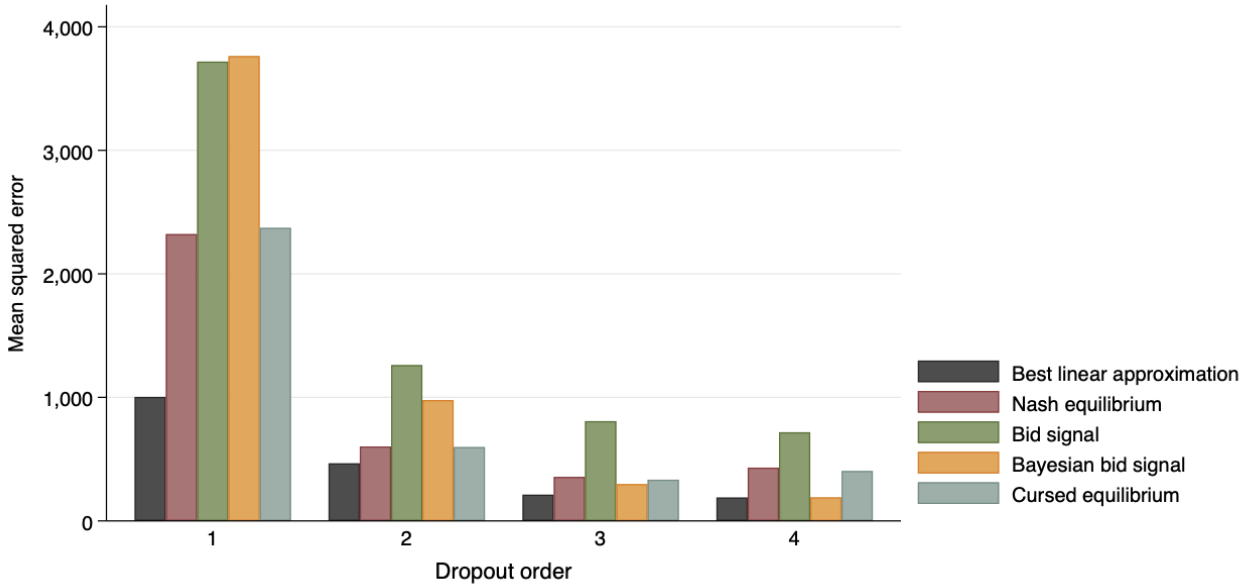
⁴⁷Note that all models are in fact linear models. Derivations are available on request.

dropout order is the most interesting, as this is based on the bids which determine the auction revenue.

Horse race for the AV

We start by comparing bidding behavior in the AV to the benchmarks. At this stage, we consider four models. We compare the Nash equilibrium benchmark and three naïve models: i) bidders exactly bid their signal, ii) Bayesian bid signal, where bidders suffer from the winner’s curse, but do take the base rate into account, as in [Goeree and Offerman \(2003b\)](#), and iii) bidders in cursed equilibrium as proposed by [Eyster and Rabin \(2005\)](#), with an estimated $\hat{\chi} = .0578$. Next to it, we provide the mean squared error of the linear benchmark at each dropout order, where only the private information signal is observable by bidders.

Figure 6: Mean squared error of model predictions in the AV

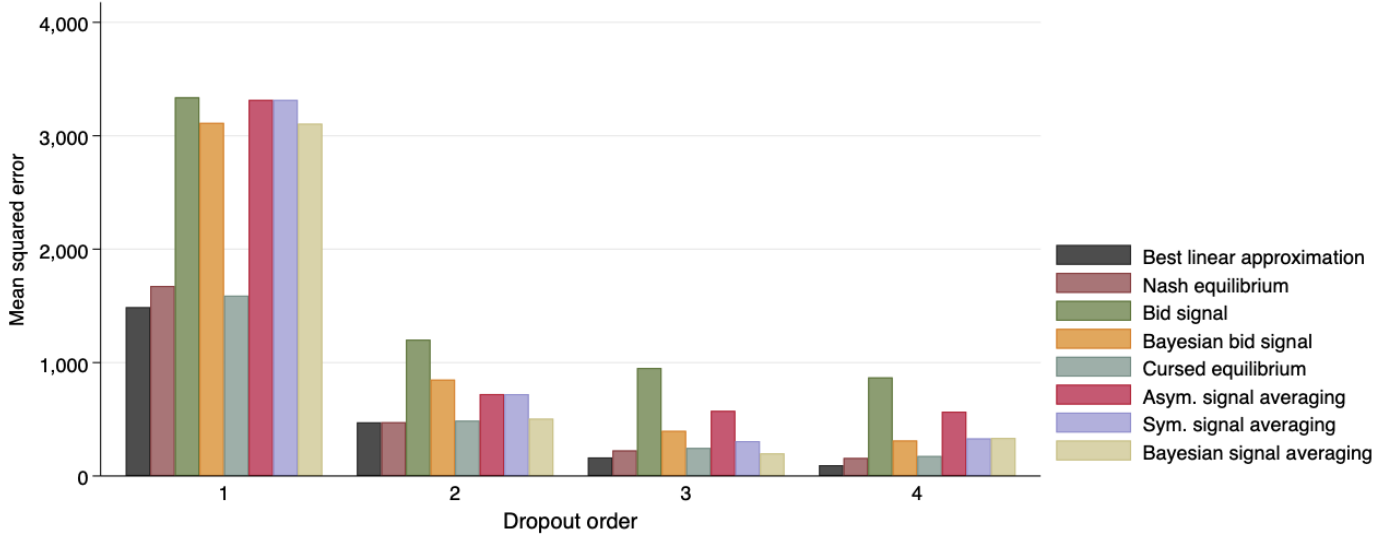


The first key insight is the fact that bidding behavior at early dropout orders is substantially less well predicted, as the mean squared error of the benchmark is much larger for early dropout orders than for late dropout orders. This decrease in the error in dropout orders also holds for most other models considered. Second, especially for the later dropouts, Bayesian bid signal shows the lowest error, and comes very close to the benchmark prediction error.

Horse race for the JEA

We now continue this analysis for the JEA, using the identical classification procedure. We incorporate all models tested above.⁴⁸ Additionally, information revelation allows us to evaluate naïve models where bidders incorporate others' bids. For this, we test three signal averaging rules. In these rules, bidders are bidding the average of all signals available, both the private information signal as well as signals inferred from opponents' bidding behavior. The symmetric signal averaging rule, originally introduced by Levin et al. (1996), uses that bidders assume that also their opponents apply such a signal averaging rule. The Bayesian signal averaging rule is additionally applying information on the prior, similar to the difference between bid signal and Bayesian bid signal-rules for second-price auctions. The asymmetric signal averaging rule assumes that other bidders bid their signal, thus allows for straightforward computations. For the JEA, the best linear approximation incorporates all bids at earlier dropout orders, as these are observable when deciding on a bid.

Figure 7: Mean squared error of model predictions in the JEA



The main pattern observed in the AV carries over to the JEA: later bids can and in fact are predicted more precisely. Compared to the AV, the prediction error is much lower in the JEA at late dropout orders, suggesting that bidding behavior is more predictable at this point (e.g., the best linear approximation for the fourth dropout shows a mean squared error of 189.5 in the AV and 96.1 in the

⁴⁸For this auction format, we estimate $\hat{\chi} = -0.137$.

JEA). At early dropout orders, there is however more noise in the JEA than in the AV. This might complicate matters for remaining bidders trying to estimate the value based on this revealed information in the JEA.

Interestingly, Nash equilibrium fits bidding behavior quite well, when comparing the mean squared error to the benchmark error of the regression.⁴⁹ Within the signal averaging rules, the Bayesian signal averaging rule performs best. Note that all signal averaging rules imply low intercepts in the linear bidding model, and we have presented evidence for substantial intercepts in the main text. This contributes to the high errors found for all signal-averaging rules.

B.2.1 Bid classification tables

Below are tables showing distances to predictions based on observed bidding, by dropout order.

⁴⁹Note that the simulated Nash equilibrium bids, as well as all other models incorporating observed dropouts, are based on inverting observed bids to retrieve the underlying signal. To do so, these rules make assumptions about how other bidders form their bids. This often leads to inferences about other bidders' signals which are incorrect, as other bidders did not, in fact, bid exactly as predicted by these models.

Table 9: Classifying bids into models

	AV	JEA		AV	JEA
First dropout			Third dropout		
Nash	2321.8	<i>1675.4</i>	Nash	356.3	225.8
Bid signal	3718.3	3339.3	Bid signal	807.5	952.6
Bayesian bid signal	3763.3	3114.3	Bayesian bid signal	298.1	398.6
χ cursed	<i>2372.2</i>	1590.5	χ cursed	333.3	248.1
Sym. signal average		3316.7	Sym. signal average		307.8
Asym. signal average		3316.7	Asym. signal average		575.2
Bay. signal average		3106.6	Bay. signal average		200.3
Best linear approx.	1004.0	1489.3	Best linear approx.	212.2	163.9
Second dropout			Fourth dropout		
Nash	<i>602.3</i>	474.7	Nash	431.5	159.3
Bid signal	1261.3	1202.6	Bid signal	717.7	869.7
Bayesian bid signal	978.8	850.3	Bayesian bid signal	190.3	313.5
χ cursed	597.6	<i>488.2</i>	χ cursed	404.0	<i>176.4</i>
Sym. signal average		722.3	Sym. signal average		331.6
Asym. signal average		722.9	Asym. signal average		567.4
Bay. signal average		505.6	Bay. signal average		335.6
Best linear approx.	465.9	473.5	Best linear approx.	189.5	96.1

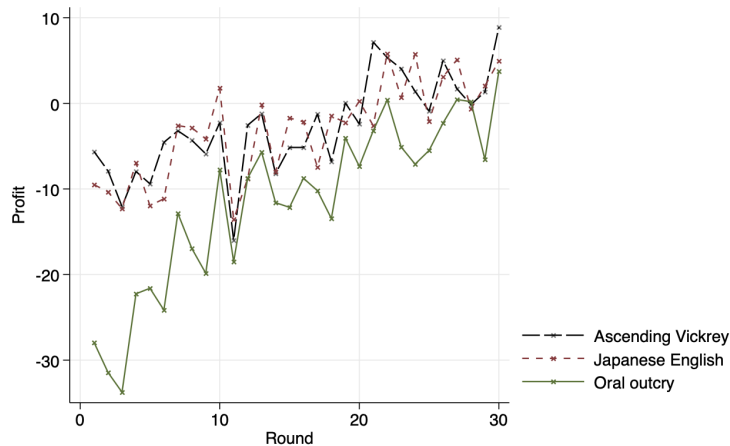
Note: Average distance of observed bids to all considered models, by auction format and dropout order. Distances are squared distance from observed bid to bid predicted by each model. The best fitting model's distance is in bold, models within 10% of the best model's fit are italicized.

B.3 Learning effects

Information revelation in auctions potentially affects how bidders learn over time. In open auctions, this learning might also take place during the auction itself, and before information is revealed in sealed bid auctions, at the end of an auction.

In Figure 8 we plot the evolution of the winning bidders' profits over rounds, by auction format.

Figure 8: Evolution of profits over rounds by auction format



There is learning in the sense that profits increase over rounds. However, there are no meaningful differences in the evolution of profits between the JEA and the

AV, learning in the OO is strongest in the sense of increases in profits over time. As we discuss in the main text, our results on revenue continue to hold in our auction data separately both in the first and last 15 rounds.

B.4 Estimations with experienced bidders

In the following, we present results of repeating estimations we report in the main text when only using the second half of our data, rounds 16 to 30.

In Table 3 in the main text, we study how available information correlates with bids. Table 10 repeats this analysis for rounds 16-30.

Table 10: Bidders' use of information in JEA

	(1) $d_{i,1,g,t}$	(2) $d_{i,2,g,t}$	(3) $d_{i,3,g,t}$	(4) $d_{i,3,g,t}$	(5) $d_{i,4,g,t}$	(6) $d_{i,4,g,t}$	(7) $d_{i,4,g,t}$	(8) $V_{g,t}$	(9) \widehat{BR}
	Observed	Observed	Observed	Observed	Nash	SA	BSA		
$s_{i,t}$	0.329*** (0.078)	0.274*** (0.057)	0.179*** (0.047)	0.149*** (0.035)	0.287 (0.000)	0.250 (0.000)	0.168 (0.000)	0.232*** (0.040)	0.290*** (0.001)
$d_{1,g,t}$		0.341*** (0.063)	0.038 (0.026)	0.029* (0.015)	0.100 (.)	0 (.)	0 (.)	-0.010 (0.035)	0.017*** (0.005)
$d_{2,g,t}$			0.537*** (0.089)	-0.010 (0.019)	0.167 (.)	0 (.)	0 (.)	-0.011 (0.057)	0.047*** (0.008)
$d_{3,g,t}$				0.641*** (0.088)	0.333 (.)	0.750 (.)	0.832 (.)	0.302*** (0.085)	0.143*** (0.009)
Round	-0.592 (0.522)	0.201 (0.423)	0.288 (0.163)	-0.063 (0.140)				0.379* (0.187)	-0.041*** (0.007)
Constant	35.745* (17.143)	34.694*** (10.104)	23.235*** (5.317)	26.580*** (4.495)	11.265 (.)	0 (.)	0 (.)	41.700*** (6.651)	50.207*** (0.597)
Observations	300	300	300	300				300	300
Adj. R^2	0.167	0.394	0.751	0.833				0.370	0.988
Rounds	16-30	16-30	16-30	16-30				16-30	16-30
Estimation	FE	FE	FE	FE				OLS	OLS

Notes: $d_{j,g,t}$: dropout at order j in group g and round t ; $V_{g,t}$: common value; $s_{i,t}$: signal of bidder i . (1) to (4) are fixed effects estimates (within estimation) of information use. Dependent variables are dropouts at each order, e.g. (1) are all bidders dropping out first in an auction. Regressors are the available information at each dropout. (5) to (7) show how information is used in three canonical models, only for the fourth dropout. SA refers to the signal averaging-rule, BSA to the Bayesian signal averaging-rule. Note that these show how bids respond to earlier bids, where these bids are also calculated to follow the theoretical models. (8) shows how the price-setting bidder would have to use information to predict the common value after observing three dropouts. (9) shows how the bidder dropping out fourth would weigh information in an empirical best response. We provide adjusted R^2 of the original within-estimated model, as well as from estimating standard OLS where we include subject-specific absorbing indicators. The latter also includes fit obtained from subject fixed effects. Standard errors in parentheses, clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Across dropout orders, bidders appear to rely relatively less on public dropouts, and relatively more on their own private signal in late rounds. (8) shows that observed bids are more informative in late rounds than in the full data set. However, bidders still rely too strongly on the observed dropouts than what the empirical

best response in (9) suggests.

In Table 4, we study whether separately elicited characteristics of subjects correlate with the fixed effect we estimate from bidders' information use. Table 11 repeats this with experienced bidders.

Point estimates are comparable to the analysis with the full data set in the main text. There are some estimates with larger standard errors, e.g. we cannot reject anymore that there is no interaction effect for SVO in the JEA. Note however that by restricting the dataset to the last 15 rounds, we will estimate the fixed effects much less precisely, as we on average only have 3 observations per individual to estimate those. In addition, for one bidder for d_1 & d_2 , as well as for five bidders for d_3 & d_4 , we cannot obtain a fixed effect any longer, as we don't have observations at these dropout orders for these bidders.

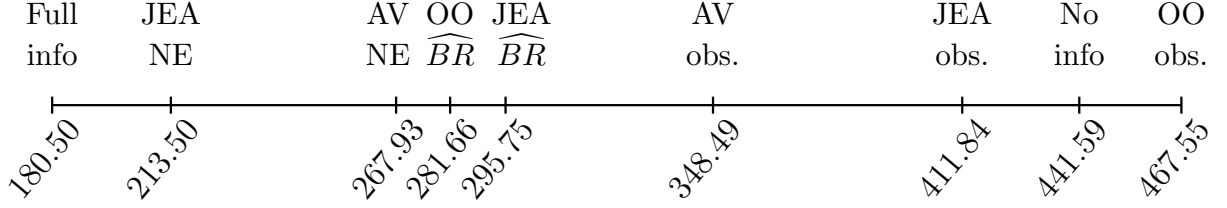
Table 11: Bidder fixed effects and their characteristics

	Average bidder fixed effect			
	d_1 & d_2		d_3 & d_4	
JEA	7.100*	(3.528)	1.534	(2.181)
SVO	0.110**	(0.041)	0.100**	(0.032)
JEA \times SVO	-0.331	(0.200)	0.017	(0.042)
Imitator	4.469	(3.509)	3.014	(1.936)
JEA \times Imitator	-5.555	(8.085)	0.165	(2.693)
Constant	0.894	(1.767)	-4.797***	(1.239)
Observations	89		85	
Estimation	OLS		OLS	

Notes: Average fixed effects from regressing bids on available information for first and second vs. third and fourth dropout; pooling data from the AV and the JEA. SVO is a subject's social value orientation, in degrees. Imitator is a dummy variable equal one if a subject chose to retrieve social information when this contains no valuable information on the true state. Standard errors in parentheses, clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Figure 4 in the main text we plot squared distances from the value to the prices in the auction and to some benchmarks, respectively. In Figure 9, we show this based on auction rounds 16 to 30. We observe some learning, as distances decrease compared to the analysis in the main text. This is strongest for the OO, where distances move closer to the no information benchmark, and bids in the empirical best response reveal more information than they do in the JEA.

Figure 9: Squared distance to common value, rounds 16 to 30



In Table 5 in the main text, we investigate the effect of jump bids. In Table 12, we repeat this analysis for rounds 16 to 30. Effects of jump bidding appear to be somewhat more pronounced in the second half of the data. In particular, we now estimate a significant negative effect of jump bids on winners' profits, suggesting that jump bidding is an even less profitable strategy after bidders gained experience.

Table 12: Effect of jump bids in the OO, rounds 16-30

	(1)	(2)	(3)	(4)
	Jump bid	Pr(win)	Mean earnings	Winners' profits
Jump bid (IV)		0.226*** (0.055)	-0.058*** (0.018)	-0.131*** (0.039)
$s_{i,t}$	0.331*** (0.034)	0.199*** (0.045)	-0.004 (0.011)	-0.111*** (0.029)
t	0.122 (0.310)		0.083* (0.045)	0.526** (0.264)
$V_{g,t}$			0.144*** (0.023)	0.716*** (0.105)
Constant	26.054** (10.474)	-15.425*** (3.963)	-12.948*** (2.334)	-64.111*** (10.498)
Observations	703	703	703	153
Estimation	OLS	2SLS	2SLS	2SLS

Notes: Jump bid is the increment of a bid beyond the current price at the moment the bid was submitted. In 2SLS, we instrument the total jump bid per bidder with the jump bid at a price of 0. $s_{i,t}$ is the submitting bidder's signal in round t . $V_{g,t}$ represents the common value. Standard errors in parentheses, clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.5 Information usage in the AV and the JEA

In Section 6.2, we describe an empirical best response \widehat{BR} in the JEA. It relies on estimated signals. Table 13 shows results of regressing signals on bids, which we in turn use to predict signals based on observable bids, where $s_{j,g,t}$ refers to the

signal of the bidder dropping out in j -th order in group g , round t , and $\widehat{s_{j,g,t}}$ refers to the predicted signal of the bidder dropping out in j -th order.

Table 13: Predicting signals with observed bids

	(1)	(2)	(3)
	$s_{1,g,t}$	$s_{2,g,t}$	$s_{3,g,t}$
$d_{j,g,t}$	0.205** (0.064)	0.567*** (0.089)	1.009*** (0.087)
$\widehat{s_{1,g,t}}$		0.048 (0.191)	0.081 (0.226)
$\widehat{s_{2,g,t}}$			-0.147 (0.140)
t	0.270 (0.202)	0.177 (0.175)	0.166 (0.140)
Constant	68.089*** (4.111)	33.977** (11.964)	5.797 (13.079)
Observations	600	600	600
Adjusted R^2	0.031	0.213	0.342
Rounds	1-30	1-30	1-30
Estimation	OLS	OLS	OLS
Session FE	Yes	Yes	Yes

Notes: Standard errors in parentheses and clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 14, we show estimation results of regressing dropouts on information using fixed effects estimation, pooling data from the AV and the JEA. Note that as signals are correlated in this experiment, some correlation in bids are also expected in the AV, even though dropouts are not observable. In Table 14, this explains why when regressing $d_{i,j,g,t}$ on $d_{j-1,g,t}$ yields significant positive coefficients.

To establish that information is being incorporated, we can interact the available information with treatment dummies. In Table 14, we confirm that observed dropouts are more strongly correlated with bids in the JEA than in the AV, as the interaction effects for the just preceding dropout are positive and significant. This suggests that revealing information actively influences bidding behavior.

Table 14: Comparing information use in the AV and the JEA

	$d_{i,1,g,t}$	$d_{i,2,g,t}$	$d_{i,3,g,t}$	$d_{i,4,g,t}$
$s_{i,t}$	0.247*** (0.0457)	0.297*** (0.0216)	0.242*** (0.0224)	0.227*** (0.0298)
$d_{1,g,t}$		0.285*** (0.0309)	-0.00113 (0.0172)	-0.0141 (0.0209)
$d_{2,g,t}$			0.357*** (0.0319)	-0.0114 (0.0317)
$d_{3,g,t}$				0.465*** (0.0440)
Round	-0.498*** (0.155)	-0.0381 (0.0872)	-0.126** (0.0596)	-0.174*** (0.0341)
JEA $\times s_{i,t}$	0.0464 (0.0718)	-0.0296 (0.0398)	-0.0704* (0.0342)	-0.109*** (0.0336)
JEA $\times d_{1,g,t}$		0.0871* (0.0463)	0.0244 (0.0243)	0.0392 (0.0253)
JEA $\times d_{2,g,t}$			0.195*** (0.0533)	-0.0271 (0.0479)
JEA $\times d_{3,g,t}$				0.244*** (0.0827)
JEA \times Round	0.181 (0.315)	-0.0844 (0.141)	0.0433 (0.0937)	0.0991** (0.0455)
Constant	32.09*** (4.573)	38.94*** (1.653)	37.14*** (1.969)	33.30*** (2.440)
Observations	1199	1199	1199	1199
Adjusted R^2	0.135	0.502	0.732	0.777
Estimation	FE	FE	FE	FE

Notes: Standard errors in parentheses and clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.6 Informational impact of dropouts

In this section, we investigate the informational impact of earlier bids on subsequent bids. To do so, we first regress bids, by dropout order, on public information, and then predict residuals. As this estimation by design excludes all private information, for example a bidder's signal or bidders' idiosyncratic characteristics, this variation will be captured in the residual. Below, we reproduce the estimation used to predict residuals, we do use matching group fixed effects in this estimation.

Table 15: Residual estimations

	$d_{i,1,g,t}$	$d_{i,2,g,t}$	$d_{i,3,g,t}$
$d_{1,g,t}$		0.477*** (0.0385)	0.0221** (0.00955)
$d_{2,g,t}$			0.665*** (0.0435)
Round	-0.555 (0.318)	-0.148 (0.108)	-0.0479 (0.0949)
Constant	77.19*** (4.930)	60.20*** (2.747)	36.93*** (4.435)
Observations	600	600	600
Adjusted R^2	0.113	0.419	0.698
Fixed effects	matching group	matching group	matching group
Estimation	OLS	OLS	OLS

Notes: Standard errors in parentheses and clustered at the matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We then regress dropouts at later dropout orders on these residuals, results are reported in Table 16. Doing so, we can estimate the impact of information revealed in earlier bids on later bids, where we isolate the information contribution of each observed bid. For comparison, we repeat this exercise for Nash equilibrium and the Bayesian signal-averaging rule.⁵⁰

In (1) to (3), we observe that the effect of a bidder's private information, captured by $s_{i,t}$ is less than the public information, revealed through the dropouts. As in the analysis in the main text, we see that the just preceding dropout carries most weight in explaining bidding behavior. This does not lend support to bidders suffering from a strong correlation neglect, as we would expect higher coefficients on the impact of earlier residuals in that case (e.g., on $e_{1,g,t}$). Similarly, bidders' private information, $s_{i,t}$, is weighted less than in the benchmarks.

⁵⁰In predicting corresponding residuals, we do not use matching group fixed effects nor do we control for round. For this estimation, note that the residuals are obtained from regressing simulated bids on simulated bids.

Table 16: Information effects captured by residuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Observed			Nash equilibrium			Bayesian signal-averaging		
	$d_{i,2,g,t}$	$d_{i,3,g,t}$	$d_{i,4,g,t}$	$d_{i,2,g,t}$	$d_{i,3,g,t}$	$d_{i,4,g,t}$	$d_{i,2,g,t}$	$d_{i,3,g,t}$	$d_{i,4,g,t}$
$s_{i,t}$	0.272*** (0.0220)	0.168*** (0.0211)	0.120*** (0.0180)	0.575*** (0.00000261)	0.431*** (0.00000411)	0.287*** (0.00000549)	0.253*** (0.00000220)	0.202*** (0.00000475)	0.168*** (0.00000568)
$e_{1,g,t}$	0.401*** (0.0392)	0.286*** (0.0186)	0.250*** (0.0134)	0.200*** (0.00000342)	0.354*** (0.00000524)	0.491*** (0.00000515)	0.747*** (0.00000366)	1.057*** (0.0000154)	1.220*** (0.0000112)
$e_{2,g,t}$		0.566*** (0.0455)	0.429*** (0.0328)		0.250*** (0.0000102)	0.458*** (0.00000744)		0.798*** (0.0000198)	1.218*** (0.0000204)
$e_{3,g,t}$			0.719*** (0.0710)			0.333*** (0.0000234)			0.832*** (0.0000370)
Constant	60.04*** (2.940)	78.92*** (2.711)	90.86*** (2.151)	37.08*** (0.000190)	49.18*** (0.000386)	63.64*** (0.000619)	65.16*** (0.000157)	69.01*** (0.000484)	74.32*** (0.000610)
Observations	600	600	600	600	600	600	600	600	600
Adjusted R^2	0.439	0.713	0.772	1.000	1.000	1.000	1.000	1.000	1.000
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Note: Standard errors in parentheses and clustered on matching group level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.7 Explaining heterogeneity in bidding

In Section 6.3, we study correlations of bidders' fixed effect with their separately elicited characteristics. A potential concern of this analysis is that these fixed effects are themselves estimated, and some might be more noisily estimated than others. To account for this, we study whether the results presented in the main text are robust to using Weighted Least Squares instead of OLS, where the weights are given by the inverse of the average variance of the estimate of each bidders' (averaged) fixed effect. This procedure ensures that particularly noisy fixed effects receive less weight in the regression. We present results in Table 17.

Table 17: Bidder fixed effects and their characteristics

	Average bidder fixed effect			
	d_1 & d_2		d_3 & d_4	
JEA	7.188***	(1.305)	3.733***	(0.998)
SVO	0.118***	(0.024)	0.007	(0.023)
JEA \times SVO	-0.349***	(0.044)	0.013	(0.033)
Imitator	5.364***	(1.030)	7.140***	(0.967)
JEA \times Imitator	-0.524	(1.983)	-5.906***	(1.593)
Constant	0.492	(0.716)	-4.631***	(0.697)
Observations	90		90	
Estimation	WLS		WLS	

Notes: Average fixed effects from regressing bids on available information for first and second vs. third and fourth dropout; pooling data from the AV and the JEA. SVO is a subject's social value orientation, in degrees. Imitator is a dummy variable equal one if a subject chose to retrieve social information when this contains no valuable information on the true state. We use weighted least squares, with the weight given by the inverse average variance of the estimate of the bidder fixed effect, averaged at d_1 and d_2 , and at d_3 and d_4 . Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We observe that the main insights presented in the main text carry over, e.g. spite appears to be particularly important for early bidding in the JEA.

B.8 Bidding in oral outcry auctions

In the main text, we use median splits on bidders' endowment effects to study whether auction fever affects bidders with strong endowment effects more strongly. For robustness, in Table 18 we present regression results of how the probability to win an auction and the profit of the winning bidder depend on the bidder's exogenously measured inclination to succumb to the endowment effect. In (1), we see that bidders suffering from a stronger endowment effect are not more often winning auctions. In (2), we see that the winners' total profits across all auctions

decrease substantially and significantly in their endowment effect.

Table 18: Quasi-endowment effect in the OO

	(1)		(2)	
	Nr. of auctions won		Winners' profits	
Endowment effect	0.352	(0.527)	-31.998**	(15.777)
Constant	6.026***	(0.549)	-76.154***	(9.761)
Observations	39		39	
Estimation	OLS		OLS	

Notes: Robust standard errors in parentheses. As there are only 4 matching groups where the endowment effect was elicited, we do not cluster standard errors in this regression (Cameron and Miller, 2015). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Online Appendix: Additional descriptive statistics

In this section, we provide some additional analyses of the data.

C.1 Questionnaire results

In the questionnaire, we offered several reasons why bidders behaved as they did, asking participants how much they agree to a statement on a 7-point Likert scale.

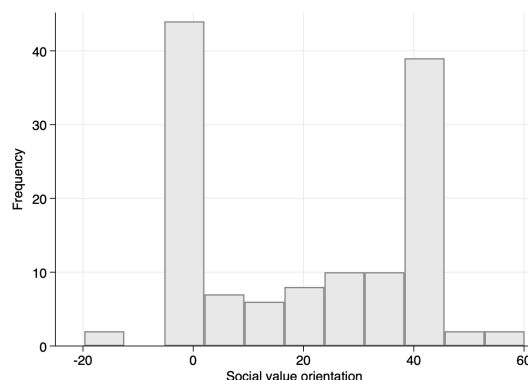
Below is the mean and standard deviation of how much people agree with a given statement. The scale is from 1 to 7, where 7 is fully agreeing, 4 is undecided.

Treatment	Statement	Mean	SD
AV	In auctions where I did not expect to win, I stayed in the auction longer to increase the price paid by the winner.	2.72	1.96
JEA	In auctions where I did not expect to win, I stayed in the auction longer to increase the price paid by the winner.	3.64	2.03
AV	In auction where I did not expect to win, I quit the auction sooner to decrease the price paid by the winner	2.98	2.00
JEA	In auction where I did not expect to win, I quit the auction sooner to decrease the price paid by the winner	3.08	1.83
JEA	When I observed other bidders leaving, I formed a more precise guess of the value of the item.	4.82	1.76
JEA	When I observed other bidders leaving, I also immediately left the auction, as I relied on the other bidders' guess of the value.	3.79	1.85
OO	All else being equal, I was more likely to enter a new bid if I have been the standing bidder for longer.	3.21	1.76
OO	All else being equal, I was willing to pay more for the item if I have been the standing bidder for longer.	3.26	1.82
OO	I tried to deter other bidders from bidding by entering a bid much higher than the current price.	4	2.12
OO	I tried to prevent other bidders from entering their desired bid by entering a bid much higher than the current price.	4.36	1.94
OO	I entered bids much higher than the current price because I thought this would allow me to pay a lower price for the item.	3.21	2.04
OO	I entered bids much higher than the current price because I was feeling impatient and wanted the auction to finish sooner.	3.15	1.95
OO	I entered bids much higher than the current price because I was becoming annoyed by being overbid by other participants.	3.26	2.11
OO	I entered bids much higher than the current price because it felt costly to decide on and enter new bids.	2.92	1.75

C.2 Circle test

We also elicited subjects' social value orientation. It is given as an angle. 0° is purely selfish (6 self, 0 other), whereas 45° is splitting equally between self and other (minimising inequality and maximising efficiency). Figure 10 gives a histogram of observed choices.

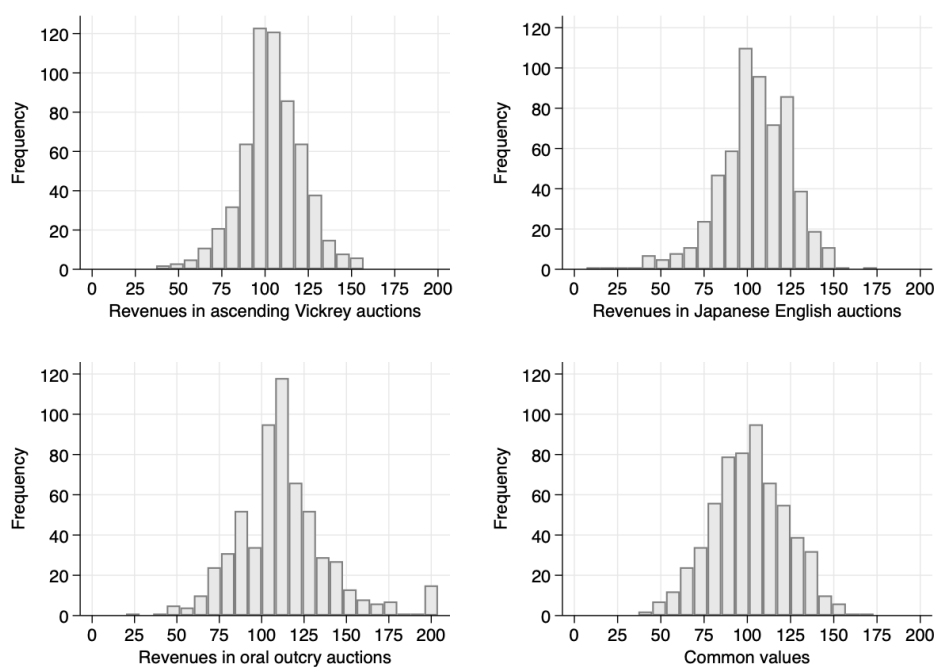
Figure 10: Angle in circle test



C.3 Histograms of auction revenues

In Figure 11, we plot histograms of the revenues in all three auction formats as well as a histogram of the common values drawn.

Figure 11: Histograms of the drawn common values and revenues.



D Online Appendix: Instructions and screenshots of the experimental interface

In the following, we reproduce the instructions for participants as well as examples of the auction screens.

D.1 Experimental instructions

Page 1 Welcome!

Welcome to this experiment. Please read the following instructions carefully. You will also receive a handout with a summary. There is a pen and paper on your table, you can use these during the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. The use of mobile phones is not allowed. If you have any questions, or need assistance of any kind, at any time, please notify the experimenter with the CALL button on the wall to your left, the experimenter will then assist you privately.

Your earnings will depend on your decisions and may depend on other participants' decisions. Your earnings will be paid to you privately in cash at the end of today's session. All your earnings will be denoted in points. At the end of the experiment, each point that you earned will be exchanged for 25 eurocents.

Page 2 Decision and Payoffs

This experiment consists of 30 periods. In each period, you will be allocated randomly to a new group of five participants. Therefore, in each period you will be in a group with (most likely) different participants. You will never learn with whom you are in a group. At the end of the experiment, five periods will be randomly selected for payment. Your earnings will be the sum of the earnings in these five periods.

Description of the situation and possible earnings

In each period, an auction will take place. In each auction, a product of unknown value will be sold. In each period, you will be given a capital of 20 points. Any profits or losses you make in this period will be added to or subtracted from this capital.

Procedures

In each auction, each of the five participants (including you) can obtain the product. First, every participant indicates that he or she is ready, and, as soon

as all participants indicate so, there will be a countdown of three seconds, after which the auction starts.

{JEA/AV: In the auction itself, the price will rise in increments of one point, starting at a price of 0. This will be indicated with a thermometer, where the level of the thermometer indicates the current price.

At any point while the price rises, you can decide to leave the auction. You do so by clicking on the “EXIT” button, indicating that you are not willing to buy the item and leave the auction for this period. For all remaining participants, the auction continues.

The auction stops after four of the five participants have pushed the “EXIT” button. The winner of the auction is the last participant remaining in the auction. The price the winner has to pay to buy the product is determined by the level of the thermometer when the fourth bidder has pushed the “EXIT” button. The price level at this point is called SELLING PRICE. The winner obtains the product and pays the SELLING PRICE. The earnings for the winner in the period are given by the value of the product minus the SELLING PRICE. These earnings are added to the capital of 20 points in this period. More details about how the value of the product is determined will follow. All participants who exited the auction will not obtain the product and will earn an amount equal to the capital of 20 points in this period.

{AV ONLY: During the auction, you will not observe how many participants remain in the auction. The price continues to rise as long as there are at least two participants in the auction including yourself.}{JEA ONLY: During the auction, you will be notified as soon as any other participant exits the auction. You will be shown at which price this other bidder left the auction, and there will be a pause of 4 seconds, in which the price will not be increasing. Afterwards, as long as there are at least two participants remaining in the auction, the price rises again.}

In the unlikely case in which multiple participants quit at the same moment and there is no bidder remaining in the auction afterwards, the program will randomly choose the person buying the item from all participants who were the last to exit and did so at the same time. The SELLING PRICE is then the level of the thermometer where these participants simultaneously pressed the button.

At the end of each period, the SELLING PRICE paid by the buyer will be shown to all participants within a group. The buyer will not literally receive a product. In addition to the capital for the period, he or she will receive an amount equal to the value of the product minus the selling price of the product (in points). The previously unknown value of the good will then be revealed to all bidders, as

well as their earnings in points in this period. Afterwards, you will be matched with a new group of bidders and a new auction starts, with the same procedure.

Example: Suppose that the first 4 bidders who exit the auction do so at prices 40, 50, 70, 80. Further assume that the product's value is 90 points. Then the last remaining bidder in the auction will receive the product and pay 80 points. His or her earnings from the auction will be $90 - 80 = 10$, and the total earnings for the period will be $10 + 20$, where 20 is the capital of the period. All other bidders will each earn the capital of 20 in that period.}

{OO: In the auction itself, participants will have the opportunity to enter maximum bids. A maximum bid tells the computer how much you maximally want to pay for the good. The computer will try to obtain the good as cheap as possible on your behalf, and at a price that is no higher than your maximum bid. If your maximum bid is the highest at some moment, then you are the current standing bidder. The standing bidder at the end of the auction obtains the product. This auction proceeds in bidding rounds in the following manner:

As soon as the auction starts, a 15 seconds countdown is initiated. Within these 15 seconds, each bidder can submit a maximum bid that is zero or higher. Whenever a maximum bid is submitted, the auction will be momentarily paused. The bidder who submitted the highest maximum bid so far will be recognized as the standing bidder. At the same time, the second highest maximum bid submitted up to this point will be the CURRENT PRICE for the good. The CURRENT PRICE will be displayed to all participants and a new bidding round immediately starts. Again, a countdown of 15 seconds is initiated, and bidders can submit new maximum bids. Any new maximum bid has to be higher than the CURRENT PRICE. The current standing bidder is notified that he is the standing bidder. He/she will only be able to submit a new maximum bid when he/she is no longer the standing bidder.

This procedure will then be repeated. As soon as new maximum bids above the CURRENT PRICE are submitted, there will be a brief pause, and afterwards a new CURRENT PRICE and standing bidder will be declared. During the bidding procedure, you will be able to see the last submitted maximum bid of each bidder (if a bidder submitted at least one maximum bid). Only the maximum bid of the current standing bidder is not revealed. Note that the bidder numbers do not enable you to identify bidders, as groups change over periods and these numbers are randomly reallocated.

Bidding will continue until no bidder in your group is willing to submit a maximum bid higher than the CURRENT PRICE, and the countdown elapses.

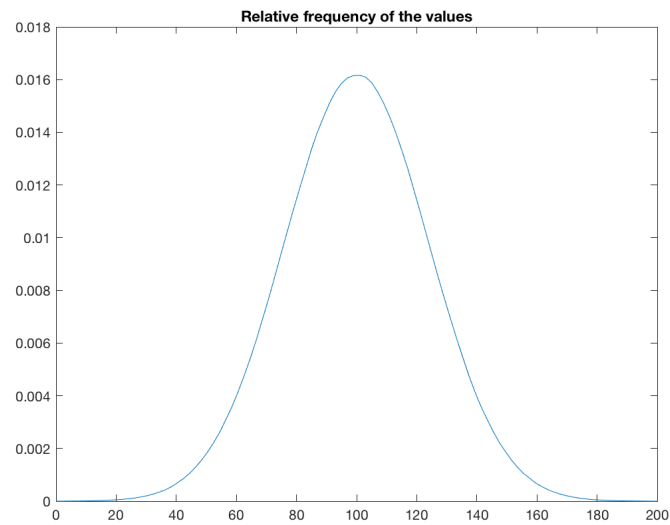
At the end of each period, so when a countdown elapses before any new bid is submitted, the earnings of the bidders are calculated as follows: The winner of the auction is the bidder who submitted the highest maximum bid, and he or she will pay a price equal to the CURRENT PRICE when bidding stopped. The buyer will not literally receive a product. He or she will receive an amount equal to the value of the product minus the CURRENT PRICE of the product (in points). This amount is added to the capital of 20 points in this period. All other bidders earn an amount equal to the capital of 20 points. The previously unknown value of the good will then be revealed to all bidders, as well as their earnings in points in this period. Afterwards, you will be matched with a new group of bidders and a new auction starts, with the same procedure. Notice that the winner of an auction can make a gain or a loss. A loss occurs if the price paid is higher than the value. Even though the final standing bidder pays a price equal to the second highest maximum bid, such bid may be high and result in a high price.}

In total, there will be 30 periods, and five randomly determined periods will be chosen to be paid out. Your earnings for the experiment will be equal to the sum of your earnings in these 5 periods.

Page 3 Value of the product and signals

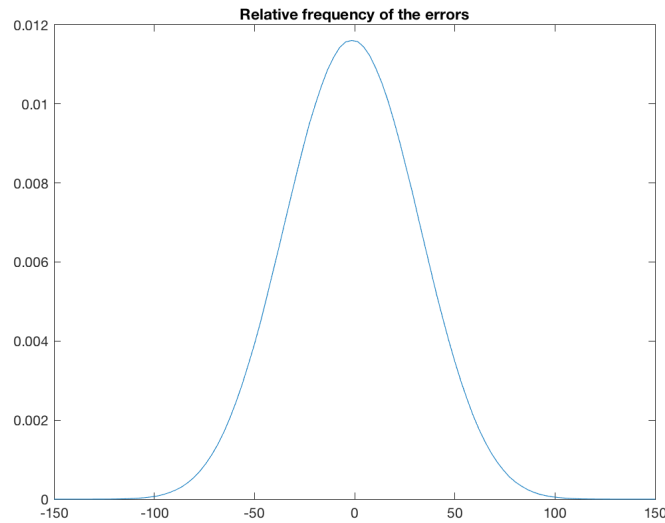
The value of the product is a random number which changes in each period. You cannot learn anything about subsequent value draws from previously observed values. Within the period the value is identical for all participants in the group. At the time of bidding, this value is unknown to all participants. Instead, each participant receives a signal which provides an imprecise indication of what the value may be. In the following, we will describe how the values and signals are determined in each period.

In each period, the value of the product will be randomly determined. The value can be any round number between 0 and 200. The figure below clarifies how frequently different values occur. You can see that values close to 100 occur most often (the frequency is highest when the value on the horizontal axis equals 100). Values below 100 occur as frequently as values above 100. Also, values below 50 occur as often as values above 150. You do not need to be familiar with such a distribution to participate in this experiment, and you will see some typical value draws on the next page.



The signals

Each participant will receive a (different) signal of the value. This signal gives a first indication of the value of the product in that period, although this is only imprecise information. In particular, the signal is the sum of the value and an error. The figure below shows how frequently different errors occur. You can see that errors close to 0 occur most often, and that errors below 0 occur as frequently as errors above 0.



The error (most likely) differs for every participant. Therefore, each participant in your group will (most likely) obtain a different signal of the value, even though the value of the product is the same for everyone. Signals higher than the value occur as frequently as signals lower than the value. Signals closer to the value are more likely than signals further away from the value. In this experiment, you will encounter only values and signals between 0 and 200.

Notice that each signal in a group is informative about the value of the product. If other bidders let their bidding depend on their signal, then their bidding will be informative about the value of the product.

Note that the signals will be newly determined in each period, therefore only the signals of this period are helpful for you to determine the value of the product for sale.

Payment

As mentioned before, out of the 30 periods, 5 will be randomly selected. You will receive the sum of the points that you earned in each of the 5 selected periods. In each period, every bidder receives a capital of 20 points. Then, any gains or losses a participant made in this period's auction are added to or subtracted from the capital. Notice that the buyer in a period can make a gain but also a loss. If the buyer pays a price higher than the value of the product, he or she makes a loss. Just like a profit is automatically added to the capital, a loss will automatically be subtracted.

Page 4 We will now illustrate in one particular example how the auction process works. We emphasize that this is only an example, and that these numbers are

not relevant for the real auctions in which you will participate afterwards.

Example

First, a value of the product is randomly determined, but not revealed to the participants. In our example, this value will be 121. Then, based on the value of 121, the signal for each participant will be drawn. The following signals are drawn: one bidder receives a signal of 60, one bidder a signal of 87, one bidder a signal of 126, one bidder a signal of 144 and the last bidder a signal of 175. Now the auction starts. {JEA/AV: The thermometer starts at 0, and rises continuously as soon as every participant indicated that he or she is ready and the countdown is initiated.

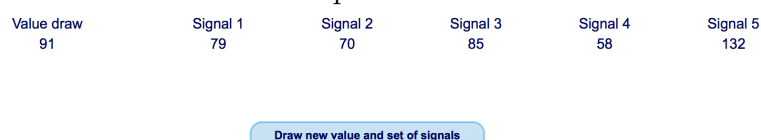
As the thermometer rises, bidders may decide to press the “EXIT” button and leave the auction. Imagine that the first participant exits at a price of 52, the second participant at a price of 77 and the third participant quits at a price of 109. Now, there still remain two bidders in the auction. {IN JEA: Each time a participant quits, all remaining participants will be notified about this, and will receive information about the price at which this participant chose to exit.} The thermometer will keep rising up to the point where the fourth bidder presses the “EXIT” button, for example at a price of 115. Then, the last remaining bidder buys the product at the selling price of 115. In this example, the product’s value was 121 points. Therefore, the winner will earn $121-115=6$ points in addition to his or her capital in this period, hence $6 + 20 = 26$ points in total, if the period is selected for payment.} {OO: The countdown starts at 15 seconds, and is initiated as soon as every participant indicated that he or she is ready. Then, imagine that the first participant to enter a bid submits a maximum bid of 52. This bidder becomes the new standing bidder. As so far only one maximum bid has been submitted, the CURRENT PRICE will be 0, and this is shown to all bidders as soon as the next bidding round commences. The countdown is reset and starts immediately. Then, imagine a new maximum bid of 77 is submitted. As this is the current highest maximum bid, this bidder becomes the new standing bidder. The second highest maximum bid at this point is 52, and therefore 52 is the new CURRENT PRICE. Bidding continues in this fashion until the countdown elapses. For example, imagine that in the next rounds maximum bids of 109, 115 and 120 are, and in the next bidding round the countdown elapses. Then, the bidder who submitted the highest maximum bid (i.e. the bidder who bid 120) will win the auction. This bidder will pay the last CURRENT PRICE, which equals the second highest maximum bid (115 in this example). In this example, the product’s value was 121 points. Therefore, the winner will earn $121-115=6$ points in addition of

his or her capital in this period, if the period will be selected for payment.}

Page 6 Practice draws

Now, you have the opportunity to see how typically values and corresponding signals are drawn. You can click on a button to draw new values and signals. Then, you will be shown a value and set of signals drawn according to the same procedure as those in the experiment. In the experiment, you will not be able to observe the value draw, but instead you receive one of the imprecise signals of the value. Five signals corresponding to this value are shown to you next to the value draw. When you click on the button again, a new value and corresponding set of signals will be drawn, you can repeat this as often as you like. Note that these example values and signals are not informative about the draws you will actually face in the experiment.

Figure 12: Screenshot of the practice draws from the instructions.



When you have tried a number of times, please continue to the practice questions on the next page.

D.2 Additional elicitations

For the last 14 sessions, we added two additional measures, elicited after the auctions concluded. Below are instructions for both tasks.

D.2.1 Imitation, adapted from Goeree and Yariv (2015)

Part 2

In this part of the experiment, you make an individual decision. The amount you earn depends only on your choices and your choices do not affect the earnings of other participants.

Guessing the urn

In this task, you have to guess which one of two possible urns has been selected. It is equally likely that you face a red or a blue urn. These urns contain red and blue balls as follows:

- Red urn: 7 red balls and 3 blue balls
- Blue urn: 7 blue balls and 3 red balls

Information

For your decision, you have to choose to receive one of two types of information:

- Draw: The color of one randomly selected ball drawn from your urn will be shown to you.
- History: The choices of three participants from previous sessions of this experiment will be revealed to you. These three participants faced the same urn as you do, but did not receive any of the two types of information you can choose between (neither Draw nor History).

Task

After you receive this information, you have to guess which of the two urns has been selected.

Payoff

You will earn 4 points if you guess correctly which urn has been chosen.

When you continue, it will be randomly determined whether you face the red or the blue urn. In the next screen, you first choose the type of information you would like to receive, then you have to enter your guess which urn you are facing.

D.2.2 Circle test, adapted from Linde and Sonnemans (2012)

Part 3

For this part of the experiment, you have been matched with one other randomly selected participant, called OTHER. Your subsequent decision will be anonymous, no participant will know with whom they have been matched. In the end, either your or OTHER's decision will be implemented.

Choice

In this part you have to choose between combinations of earnings for yourself and the OTHER. All possible combinations are represented on a circle. You can

click on any point on the circle. Which point you choose determines how much money you and the OTHER earn. You can enter this choice on the next page.

Earnings

The axes in the circle represent how much money you and the OTHER earn when you choose a certain point on the circle. The horizontal axis shows how much you earn: the more to the right, the more you will earn. The vertical axis shows how much the OTHER will earn: the more to the top, the more the OTHER earns. The distribution can also imply negative earnings for you and/or the OTHER. Points on the circle left of the middle imply negative earnings for you, points below the middle imply negative earnings for the OTHER. When you click on a point on the circle the corresponding combination of earnings, in cents, will be displayed in the table to the right of the circle. You can try different points by clicking on the circle using your mouse. Your choice will only become final when you click on the “send” button.

Payoff

The OTHER is presented with the same choice situation. At the end of the experiment, either your decision or the decision of the OTHER will be paid. This will be determined by a random draw, your decision is as likely to be chosen as the decision of the OTHER. This draw is not affected by the choices you or others make.

D.3 Screenshots of the interface

In the following, some screenshots of the screens of auction participants for all three treatments:

Figure 13: Screenshot from a ascending Vickrey auction.

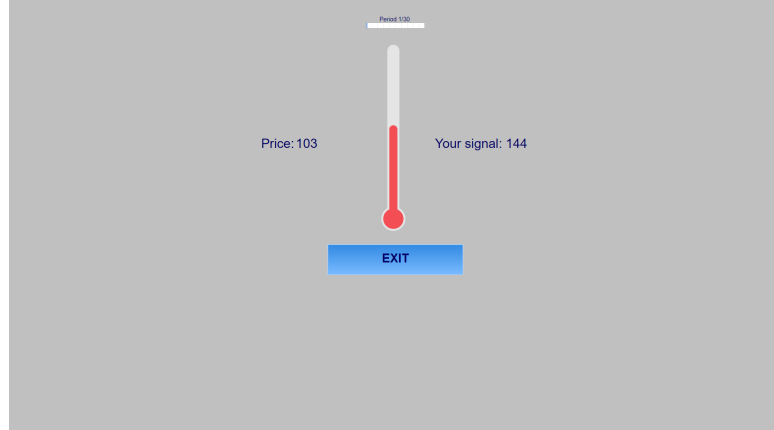


Figure 14: Screenshot from a Japanese English auction.

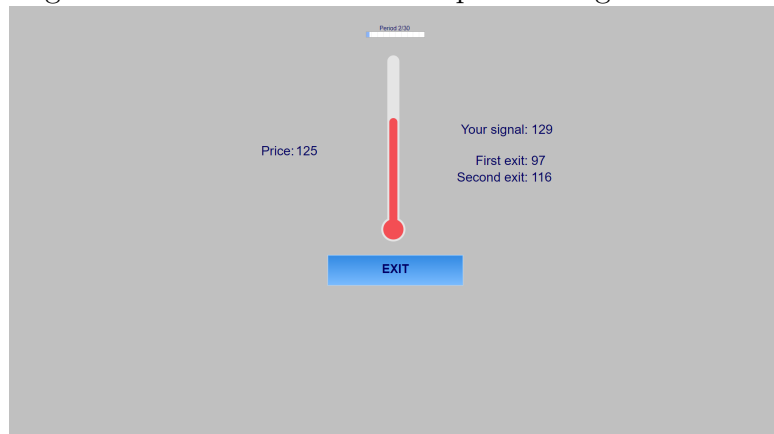


Figure 15: Screenshot from an oral outcry auction.

