# 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

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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

[1] In a policy report on the question whether the spectrum auctions ran in the UK in 2018 should use an open or sealed-bid design, PowerAuctions (2015, p. 6) writes: "..., an auction should be structured in an open fashion that maximizes the information made available to each participant at the time she places her bids (Paul R. Milgrom and Robert J. Weber, 1982a). When there is a common value component to valuation and when bidders' signals are affiliated, an open ascending-bid format may induce participants to bid more aggressively (on average) than in a sealed-bid format, since participants can infer greater information about their opponents' signals at the time they place their final bids." In a footnote they explain that the text is quoted from Ausubel (2004), and add that "Its assessment is typical of the consensus of the auction literature today." The NERA (2017) report also favors an open ascending auction and echoes the same view on page 11: "Auction theory tells us that price discovery can ease common-value uncertainty, and encourage bidders to bid a higher proportion of value ...".

award the item during the auction to the bidder who submits the highest standing 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.

[2] Probably 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).

However, such data has severe limitations. First, the direction of causality is unclear. 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. One factor that contributes to this finding is that some bidders with a low signal display spiteful behavior and stay in the auction longer than they would in the ascending Vickrey auction. 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.

[3]Nevertheless, 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 Iriberri (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. Changing the price-rule and the auction format across treatments simultaneously complicates identifying the effect that information aggregation has on the outcomes. As a result, their paper remains silent about the extent to which the endogenous information revealed in the Japanese-English auction allows bidders to actually aggregate information. On an individual bidder level, they cannot use the sealed-bid auction as a benchmark to measure the degree of information processing in the Japanese-English auction. Their focus is more on a revenue comparison of their two auction formats, instead of evaluating the extent to which information is aggregated empirically. Shedding light on this phenomenon is a key contribution of our paper. We also contribute by showing that bidders process revealed information, as our design allows to compare Japanese-English and second-price sealed-bid auctions that only differ in the observability of information. Levin et al. (1996) only provide evidence that bids correlate with previous dropouts in their Japanese-English auction, which may be driven by mechanical correlation introduced by arranging bids into order statistics (as we explain in Section 6.2). They do not, and due to the differences in pricing rules cannot, provide evidence that bids do respond to revealed dropouts. Another important difference is that their analysis does not include the Oral Outcry auction, which triggers the revenue enhancing biases that may explain their actual popularity. A less important difference 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 dropout price and disregard all other exit decisions in the Japanese-English auction.

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, 2003*a*). 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.[5]

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 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

[5] 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.

potential of the Japanese-English auction to generate endogenous information is excluded by design.

It is also instructive to contrast what can be learned from our work compared to a structural approach that uses field data. For instance, Haile and Tamer (2003) use data from Oral Outcry auctions of timber-harvesting contracts held by the U.S. Forest Service to infer information about bidders' valuations. In a private values model, they show what can be learned from two simple assumptions (i) bidders do not bid above value, and (ii) bidders do not drop out unless the price is higher than their value. Their approach allows the researchers to find bounds on the valuations of bidders. Such information is useful, for instance to investigate whether reserve prices are set optimally. In contrast, in our laboratory experiment, we observe the common value and the signals. This allows us to investigate how information is revealed, processed and aggregated in strategically more complicated common value auctions, and how this depends on the auction format. More importantly, where the structural approach takes rationality as a given, our approach makes it possible to identify potential behavioral biases. In fact, we find that behavioral biases are key to explain the popularity of Oral Outcry auctions vis-a-vis other second-price formats.

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; Ngangoué and Weizsäcker, 2021; Martínez-Marquina et al., 2019). 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), Cramton (1998)).

# 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 $V \sim N(\mu, \sigma_V) = N(100, 25)$. Each bidder $i \in \{1, 2, \ldots, 5\}$ receives a signal $X_i$ of the common value $V$. This signal is the sum of the underlying value and an individual error $\varepsilon_i$:

$$X_i = V + \varepsilon_i$$

This error is *i.i.d.* across bidders and normally distributed with mean 0 and standard deviation $\sigma_\varepsilon$: $\varepsilon_i \sim N(0, \sigma_\varepsilon) = N(0, 35)$.

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 a signal realization $x_i$ for bidder $i$. Let $Y_{i,(k)}$ represent the $k$-th highest of the signals received by any other bidder $j \neq i$, so e.g. $Y_{i,(1)}$ 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 $0, 1, 2, 3, \ldots$, 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 pays the price at which she left. In this format, a bid is the price at which the bidder decided to leave the auction.

### 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.

## 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.

[6] This 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.

## 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 $b(x_i)$:

$$b(x_i) = \mathrm{E}\left[V \mid X_i = x_i, Y_{i,(1)} = x_i\right]$$

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 $x_i$.[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):

$$b_1(x_i) = \mathrm{E}\left[V \mid X_i = x_i, Y_{i,(1)} = x_i, \ldots, Y_{i,(4)} = x_i\right]$$

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 $p_1 = b_1\left(Y_{i,(4)}\right)$. All bidders dropping out subsequently base their $j$-th bid (for $j > 1$) on their private information and the signals inferred from the $j - 1$ observed dropouts. The remaining bidders bid $b_j(x_i)$:

$$\begin{aligned} b_j(x_i) = \mathrm{E}\Big[V \mid X_i = x_i, Y_{i,(1)} = x_i, \ldots, Y_{i,(5-j)} = x_i, p_1 = b_1\left(Y_{i,(4)}\right), \ldots \\ \ldots, p_{j-1} = b_{j-1}\left(Y_{i,(5-j+1)}\right)\Big] \end{aligned}$$

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

[7] In our experimental setup with 5 bidders and normally distributed values and signals, Goeree and Offerman (2003*b*) show that the above conditional expectation is equal to: $b(x_i) = \mathrm{E}\left[V \mid X_i = x_i, Y_{i,(1)} = x_i\right] = x_i - \frac{\int_{-\infty}^{\infty} \varepsilon\, \phi_V(x_i - \varepsilon)\, \phi^2(\varepsilon)\, \Phi^3(\varepsilon)\, d\varepsilon}{\int_{-\infty}^{\infty} \phi_V(x_i - \varepsilon)\, \phi^2(\varepsilon)\, \Phi^3(\varepsilon)\, d\varepsilon}$, where $\phi_V(\cdot)$ denotes the pdf of the common value distribution, $\phi(\cdot)$ the pdf of the error distribution, with its cdf $\Phi(\cdot)$.

[8] We determine Nash equilibrium bids in our setup, using a result by DeGroot (2005, p. 167). For inferred or assumed signal realizations by bidder $i$, define $\bar{x}_i = \frac{1}{5}\left(\sum_{j=1}^{4} Y_{i,(j)} + x_i\right)$. Then in equilibrium each bidder $i$ bids: $\mathrm{E}[V \mid x_i, Y_{i,(1)}, \ldots, Y_{i,(4)}] = \frac{\frac{\mu}{\sigma_V^2} + \frac{5\bar{x}_i}{\sigma^2}}{\frac{1}{\sigma_V^2} + \frac{5}{\sigma^2}} = \frac{5\bar{x}_i \sigma_V^2 + \mu\sigma^2}{5\sigma_V^2 + \sigma^2}$. 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.

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 $\in (0, 1)$ of the bids at which they dropped out in the just described equilibrium, 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, 2003*b*): $b(x_i) = x_i$, 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 $j-1$ bidders dropped out, with the vector of revealed signals being $\mathbf{Y}_i = \{Y_{i,(4)}, \ldots, Y_{i,(5-j+1)}\}$, this implies the following bid: $b_j(x_i, \mathbf{Y}_i) = \frac{1}{j}x_i + \frac{1}{j}\sum_{k=1}^{j-1} Y_{i,(5-k)}$.[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

[9] Bikhchandani 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.

[10] Note that this rule can be plugged in iteratively, such that bidding depends only on the most recent dropout, which is an average of all previously revealed signals. This yields $b_j(x_i, b_{j-1}) = \frac{1}{j}x_i + \frac{j-1}{j}b_{j-1}$.

prior distribution of the value, and thereby accommodate (i), incorporating information on the prior. This would lead to a 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: $b(x_i) = E[V|x_i] = x_i - E[\epsilon_i|x_i]$. Goeree and Offerman (2003$b$) show that $b(x_i) = \frac{\sigma_V^2 x_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$. According to the "Bayesian signal averaging rule", bidders combine Bayes rule with the symmetric signal averaging rule.[11] After $j - 1 > 0$ observed dropouts, bidder $i$ calculates the average of available signals $\bar{x}_i = \frac{1}{j}x_i + \frac{1}{j}\sum_{k=1}^{j-1} Y_{i;(5-k)}$ and bids $b(\bar{x}_i) = \frac{\sigma_V^2 x_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}$.

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 |

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.2, 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

[11] A 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.

[12] Note 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.

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.

# 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.

[13]Note 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.

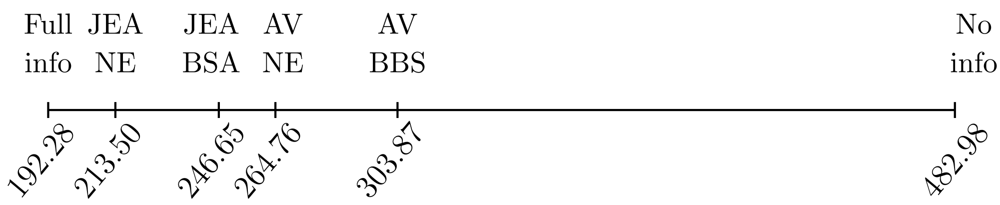
The possibility of perfect inference is curtailed by the noisiness of the signals. We account for the maximal information potentially available, the one contained in the five signals, by computing the Full Information benchmark. In it, all five signals are revealed and bidders bid the conditional expected 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.

Figure 1: Squared distance to common value - JEA and AV




[14]It 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.

[15]This 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 B, 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 e 0.25 for each point. Subjects earned on average e 24.28 (standard deviation: 6.02, minimum earnings were set to e 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 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,

[16]In 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.

[17]We discarded a set of draws whenever a common value or signal exceeded our bounds. This occurred for 0 out 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.

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 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

[18] Question 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?"

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 A.7. 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 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. While the theory predicts higher revenue in the JEA than in the AV, we cannot reject equality of revenues between the two formats. In both the AV and the JEA, actual revenues deviate systematically from the Nash benchmark.

[19] In 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.

[20] Treatment 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.

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

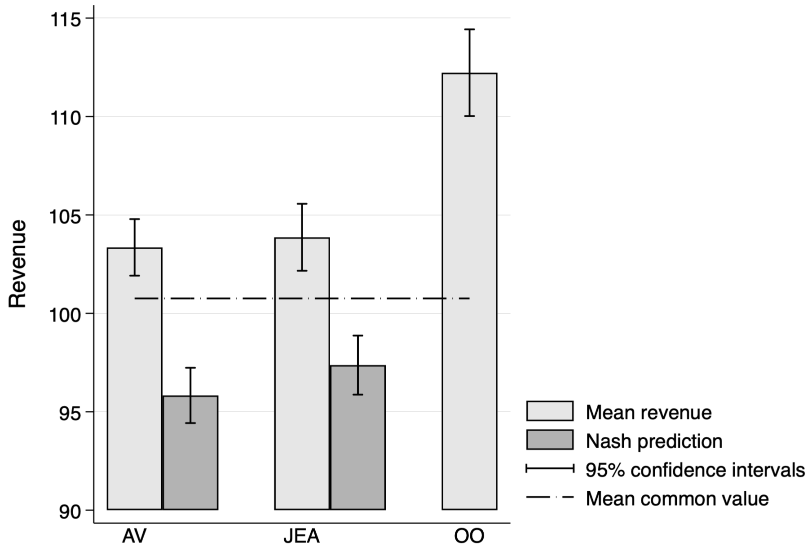



Table 2: Revenue statistics by treatment

| | | Revenue | | |
|---|---|---|---|---|
| | | Mean (Standard deviation) | | |
| Round | | 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) |
| | | Treatment effects: p-values | | |
| Round | | 1-30 | 1-15 | 16-30 |
| AV vs. | JEA | .597 | .940 | .734 |
| | OO | .003 | .011 | .049 |
| JEA vs. | OO | .009 | .003 | .059 |
| | | Revenue difference to Nash eq'm: p-values | | |
| Round | | 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.

One explanation for the failure of rejecting equality of revenues 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]

## 6.2 Information processing in JEA

We find that bidders overbid both in the JEA and in the AV compared to the rational benchmark. Our data also do not agree with the revenue prediction of (Bayesian) signal averaging, according to which revenue in the JEA must be lower compared to the AV. These findings raise the question whether subjects make use in any way of the information released in the auction. One possibility is that bidders in the JEA disregard the bidding of others and only use their private information. In this Section we show that this is not the case. We start by comparing how bids correlate in the JEA with previous dropouts, and contrast this to information use in the theoretical benchmarks. Then we proceed by showing that bidders' dropouts correlate more with previous dropouts in the JEA than in the AV, in which endogenous information of others' bids is not available.

Table 3 presents the results of a fixed-effects regression analysis that models how bids correlate with available information. Define as $b_{j;i;t}$ the dropout price of bidder $i$ in round $t$, where, for ease of exposition, $j$ denotes the dropout order corresponding to that observation. Further denote with $\mathbf{b}_{j\ \ 1;t}$ the vector collecting the $j$ 1 dropout prices preceding the $j$ $th$ bid in round $t$. For each $j$ $2$ $f1; : : : ; 4g$ we pool data for each dropout order $j$ and separately estimate the models:

$$b_{j;i;t} = \quad + \quad x_{i;t} + \gamma^{\mathsf{T}}\mathbf{b}_{j\ \ 1;t} + \quad t + \quad {}_{i} + \quad {}_{i;t}$$

where $x_{i;t}$ is the private signal of bidder $i$ and $t$ is the auction round. ${}_{i}$ is a bidder-specific fixed effect and ${}_{i;t}$ is a bidder-round error. We use the within-estimator, where we are demeaning the variables with their time-averaged counterparts. This allows us to interpret the constant as the average intercept across bidders, and each bidder's fixed effect as the deviation in this bidder's bidding level from the average.

Models (1) to (4) provide fixed effects estimates of dropout 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: Bidders' dropouts depend significantly only on their own signal and the just pre-

[21] In 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 A.5.

Table 3: Bidders' use of information in the JEA

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | $b_1$ | $b_2$ | $b_3$ | $b_4$ | | | | $V$ | $\widehat{BR}$ |
| | Observed | Observed | Observed | Observed | Nash | SA | BSA | | |
| $x$ | 0.294 | 0.267 | 0.172 | 0.118 | 0.287 | 0.250 | 0.168 | 0.250 | 0.288 |
| | (0.057) | (0.034) | (0.027) | (0.016) | (.) | (.) | (.) | (0.020) | (0.001) |
| $b_1$ | | 0.372 | 0.023 | 0.025 | 0.100 | 0 | 0 | -0.009 | 0.032 |
| | | (0.035) | (0.018) | (0.015) | (.) | (.) | (.) | (0.025) | (0.003) |
| $b_2$ | | | 0.552 | -0.038 | 0.167 | 0 | 0 | -0.003 | 0.060 |
| | | | (0.044) | (0.037) | (.) | (.) | (.) | (0.052) | (0.003) |
| $b_3$ | | | | 0.709 | 0.333 | 0.750 | 0.832 | 0.291 | 0.151 |
| | | | | (0.072) | (.) | (.) | (.) | (0.070) | (0.003) |
| $t$ | -0.316 | -0.122 | -0.083 | -0.075 | | | | 0.295 | 0.087 |
| | (0.281) | (0.114) | (0.074) | (0.031) | | | | (0.073) | (0.002) |
| Constant | 35.185 | 41.823 | 32.049 | 26.290 | 11.265 | 0 | 0 | 41.882 | 44.804 |
| | (8.628) | (2.723) | (2.933) | (3.619) | (.) | (.) | (.) | (3.799) | (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:* $b_j$: dropout price at order $j$; $V$: common value; $x$: own signal. (1) to (4) are xed e ects estimates (within estimation) of information use. Dependent variables (in columns) are dropout prices at each order, e.g. (1) are all bidders dropping out rst in an auction. Regressors (in rows) are the available information at each dropout order, i.e., the signal $x$ and the preceding dropout prices $\mathbf{b}_{j-1}$. (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 theoretical 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-speci c absorbing indicators. The latter also includes t obtained from subject xed e ects. Standard errors in parentheses, clustered at the matching group level.

ceding dropout.[22] The most recent dropout receives much more relative weight than bidders' signals. Thus, bids appear to react quite strongly to the auction proceedings.[23]

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 implied by 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 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 signifi-

[22]Conditional 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 $b_{j\ 1;t}$ yields significant coefficients on $b_{j\ 2;t}$.

[23]This 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 dropouts is double-counted in later dropouts. In the Appendix Section A.9, 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.

[24]We verified that our findings are not driven by the linear impact of information, by repeating (4) and (8) with the additional regressors $x^2$ and $(b_3)^2$. Both are not significant in either model.

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

cantly 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, 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 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

[26]In 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.

[27]Note that the positive coefficient on $t$ is a mechanical effect of all bids decreasing in $t$ (see (1) to (4)), as $V$ is in expectation constant over time. From experience, bidders learn that the amount of overbidding by others decreases over time (at the end of each round the common value of a round is communicated). To accommodate for this downward trend in the bidding, given the same previous dropouts, a bidder who estimates the common value will form a higher prediction of the common value in later rounds compared to early rounds. Such a compensating factor would have been absent if there had not been a trend in subjects' bidding. Allowing for a more flexible time trend in (8) with squared round or round fixed effects does not affect estimates on information use ($b_1$, $b_2$, $b_3$, $x$).

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] The empirical best response then equals the conditional expected value calculated on the basis of the inferred signals, under the assumptions that the other remaining bidder has a signal that equals the own signal, using the result by DeGroot (2005).[29] By assuming that the other remaining bidder has a signal that equals the own signal, the bidder beats types that are below the own type, and by doing so wins in cases where the expected profit is positive, and loses against types that are above the own type, and thereby avoids winning in cases where the expected profit is negative. Notice that the procedure is quite similar to how bidders bid in the symmetric Nash equilibrium. The difference lies in how signal are inferred from earlier bids. In the Nash equilibrium, bidders infer the signals of bidders that previously dropped out from their actual (Nash equilibrium) bidding strategies. In our empirical best response, signals are estimated from previous dropouts. 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.[30]

Importantly, this analysis in itself does not provide evidence that bidders actively incorporate information. This is the case as the regressions in Table 3 organize bids into order statistics and this mechanically produces some degree of correlation, even if bidders were to ignore entirely the bidding behavior of others. Given that a bidder's bid is noisy and not completely determined by the own signal, information will be conveyed in the previous dropout(s). As an illustration,

[28]We reproduce these estimations in the Appendix, Table 15.

[29]In calculating the conditional expected value, we invoke the assumption that signals inferred from previous dropouts are distributed as the true signals are (that is, conditional on the value they are $i.i.d.$, $N(0, 35)$).

[30]Note that $R^2$ is mechanically high in this regression because the best response is calculated as a linear function of the bids.

consider the case in which the previous dropout is very high, in fact higher than the expected current dropout conditional on own signal. Then, by definition, the expected current dropout conditional on previous dropout and own signal will be higher than the expected dropout level conditional on own signal only, thus leading to positive residual correlation between dropout orders.

This produces a mechanical correlation between dropouts and previous dropouts even if bidders do not pay any attention to the previous dropouts.

In order to use correlations among dropout prices as evidence for information processing, we need to move from an absolute to a comparative approach. In Table 4, we show excerpts from regressions where we pool data from the AV and the JEA and regress bids on the previous dropouts, signals, and interactions for the JEA. We refer to Table 16 in the Appendix for the full results. In the AV, where by design no information can be extracted from the unobservable bidding of others, we observe the mechanical correlation in dropout order statistics, as all coefficients on the just preceding dropouts $b_{j-1;t}$ are significant at conventional levels. Using the bidding in the AV as a benchmark, we measure the amount of information processing in the JEA by computing the additional correlation observed in the JEA compared to the AV. Table 4 shows that the slope parameters on every just-preceding bid are statistically larger in the JEA compared to the AV at each dropout order. As bids in the JEA are more strongly correlated than in the AV, we can conclude that bidders do react to the information contained in the bids of others.

Table 4: Comparing information use in the AV and the JEA

| | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|
| $b_{j-1}$ | 0.285 | 0.357 | 0.465 |
| | (0.0309) | (0.0319) | (0.0440) |
| JEA $\times$ $b_{j-1}$ | 0.0871 | 0.195 | 0.244 |
| | (0.0463) | (0.0533) | (0.0827) |
| Observations | 1199 | 1199 | 1199 |
| Adjusted $R^2$ | .502 | 0.732 | 0.777 |

*Notes:* $b_{j-1}$ denotes the just preceding dropout, e.g. it is $b_1$ for $b_2$. JEA is a dummy equal one for JEA auctions. Additional variables omitted from the table: all regressions include signal $x$, round $t$, all preceding dropouts ($b_{j-k}$ for all $k \in \{1, \ldots, j-1\}$) as well as all these variables interacted with the JEA-dummy and a constant. For the full regression results, see Table 16 in the Appendix. Standard errors in parentheses and clustered at the matching group level.

To sum up, we conclude that subjects' bidding is consistent with them paying attention and responding to the bids of others in the JEA. Compared to the empirical best response, subjects pay too much attention to the most recent dropout and underweigh their own signal. How subjects' 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 how heterogeneity in early bidding contributes to understanding this puzzle.

## 6.3 Exploring heterogeneity in bidding

In this Section, we investigate whether individual-specific characteristics correlate with bidders' behavior in early dropouts. 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 orders, subject-level fixed effects bring in significant additional explanatory power. Our finding that individual-specific characteristics matter more at early stages of bidding in the JEA agrees with the observation that deviations from the theoretical benchmark are less costly at these early stages in this auction format. For instance, a bidder who considers dropping out first may choose to overbid almost without costs: even when overbidding, the bidder can avoid winning by immediately dropping out when others do so. Likewise, if this bidder decides to drop somewhat earlier than the theoretical benchmark, this also happens almost without costs because the chances that all the others would drop before the theoretical benchmark is negligible if no other bidder has dropped out yet.

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.[31] 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 imitators, which applies to 26.9%

[31]Another 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.

of our participants.[32] 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 19.93 .

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. Crucially, identical bidders may behave differently between different auction formats, especially as behavioral motives may be differentially triggered. Note that our within-estimations impose that the average bidder fixed effects have a mean of zero. This means that any bidder's fixed effect can be interpreted as a deviation from the average bidding behavior within our sample for each treatment.

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. For the AV and the JEA separately, we then regress the averaged fixed effects on subjects' social value orientation and imitation proneness. Table 5 presents OLS estimates.[33]

In both treatments, estimates imply that imitators are willing to bid higher than non-imitators. The effects ares similar in size but only significant in the AV, which may be due to a lack of power. In any case, the fact that the bids of imitators are not higher in the JEA than in the AV hints at the possibility that this measure may not only capture a tendency to imitate but also general overbidding caused by confusion.[34] From this perspective, imitation is not a good candidate to explain differential bidding in the early dropouts between the two auction formats.

Our conjecture was that SVO would explain differences in the early bidding between the two auctions. The coefficient for SVO in column (2) of Table 5 is

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

[33] Note that the fixed effects are estimated, and thus may contain noise from the first stage in this estimation procedure. In the Appendix, Section A.10, we show that point estimates are similar using WLS, which addresses concerns that some fixed effects might be estimated more noisily than others. These observations receive less weight in variance-weighted WLS. The estimates on SVO and Imitator in (2) are significant in this specification, which suggests that the noise in estimating fixed effects may be important. Point estimates with experienced bidders are mostly similar, see Table 13 in the Appendix. The coefficient on Imitator is insignificant across specifications (1) to (3), and the coefficient on SVO is significant and positive in (3) and (4).

[34] There 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.

Table 5: Bidder fixed effects and their characteristics

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Average bidder fixed effect | | | |
| | $b_1$ & $b_2$ | | $b_3$ & $b_4$ | |
| | AV | JEA | AV | JEA |
| SVO | 0.125 | -0.202 | 0.005 | 0.027 |
| | (0.045) | (0.146) | (0.120) | (0.078) |
| Imitator | 5.699 | 5.213 | 6.528 | 1.575 |
| | (1.479) | (3.823) | (3.121) | (0.471) |
| Constant | -1.876 | 6.225 | -4.674 | -1.080 |
| | (1.919) | (2.363) | (1.678) | (2.681) |
| Observations | 50 | 40 | 50 | 40 |
| Adjusted $R^2$ | 0.031 | 0.014 | 0.048 | -0.031 |

*Notes:* Average xed e ects from regressing bids on available information for rst and second vs. third and fourth dropout. 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.

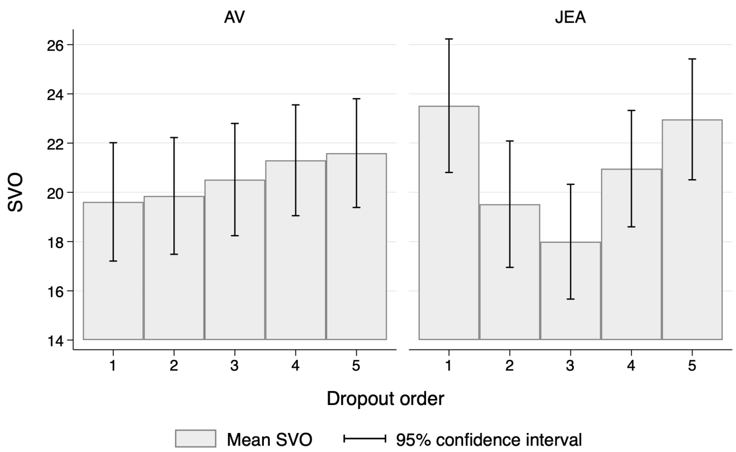
in line with the conjecture that spiteful bidders bid higher early in the JEA to drive up the price for others: only in JEA the coefficient is negative. However, the standard error is large, and we cannot conclude whether there is a negative effect or no effect of SVO on early bidding in JEA.[35]

Given that the evidence in Table 5 is not conclusive about the effect of SVO on early bidding in JEA, we looked further into how SVO affects bidding in the two auction formats. As we expected when we decided to measure SVO, competitors, those with below-median SVO, bid on average 71.3 in the first two dropouts in JEA, significantly more than in the AV where they bid on average 56.4 in the first two dropouts (Mann-Whitney U-test, 9 observations, $p$-value=0.086). This finding reflects that driving up the price for others is relatively cheap in the JEA, because this format allows bidders to enhance the price for others without much risk of actually winning the good. To put things into perspective, it is not clear that cooperators bid significantly more in the early dropouts of the JEA than in the AV (average bid of 59.6 in the AV versus 70.8 in the JEA; Mann-Whitney U-test, 9 observations, $p$-value=0.327).

[35] Somewhat surprisingly, more pro-social bidders bid slightly higher on average in the early bidding in the AV. Note that for the SVO, 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. Pro-social bidders' behavior is not significantly different in the early bidding across auctions.

Figure 3 displays for each of the two auction formats the SVO per dropout order. Whereas there is a slight increase of SVO over dropout orders in the AV, there is a surprising but intuitive pattern in the JEA: Bidders who drop out first or last have on average a higher SVO than bidders who drop out in the middle. This suggests that cooperators decide at the start to either be nice and drop out first or to go all-in in a serious attempt to win the auction. By doing so they would refrain from driving up the price for others when they do not win. In the cases where they decide to win the auction, cooperators have to outbid spiteful bidders, who are bidding more aggressively than they would have in the AV. We find that cooperators (with an SVO above the median) end up significantly more often in an extreme position (either first or last) than competitive bidders (those with an SVO below the median): Mann-Whitney U-test, 8 observations, $p$-value=0.043. This pattern only materializes in the JEA: the same test for the AV is insignificant ($p$-value=0.917, 10 observations).[36]

Figure 3: SVO by dropout order




Overall, our suggestive evidence is consistent with the following picture of how SVO may affect bidding in the two auction formats. In the JEA, spiteful bidders tend to bid higher at the start than they would have in the AV, because the information about how many other bidders are still active makes it cheap for them to overbid. Without too much risk they can stay longer in the auction and drive up the price without actually winning the object. Cooperators on the other

[36]To verify that the difference between treatments is significant, we run a logistic regression. We regress the binary dependent variable (0 if dropping out first or last, 1 otherwise) on SVO, Imitator and signal, a treatment dummy as well as interactions of all independent variables and treatment. While the coefficient on SVO is not significant ($p$-value=0.817), the coefficient on the interaction of JEA and SVO is negative and (weakly) significant ($p$-value=0.071).

hand decide at the start of the auction whether or not they want to compete and win the object for sale. If their signal makes them decide it is better not to win, they drop out early and by doing so refrain from enhancing the price for others. If they decide to compete, they relatively often end up winning the auction. In this case, they have to outbid spiteful bidders who tend to bid higher than they would have in the AV.

## 6.4 Information aggregation

Previously we showed that bidders engage in overbidding (Figure 2). Even bidders who depart from rationality can convey information in their bids, or infer information from others' bids. For instance, if bidders follow a behavioral model, then their bids will still convey information about their signals. If this is anticipated by other bidders, bidders can still process this information in their own bids. In this Section, we investigate the extent to which bidders aggregate information in the different auction formats. The measure of information aggregation is the squared distance between the price and the common value, as discussed in Section 4.

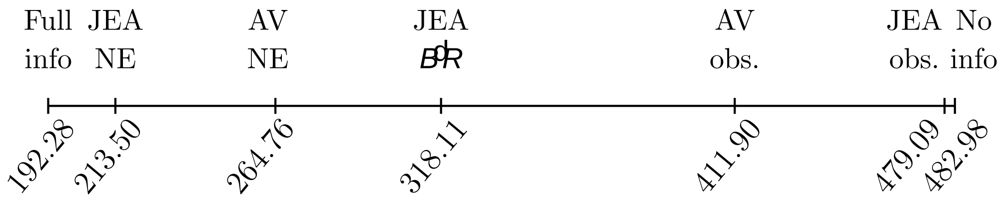
We first present a comparison between the JEA and the AV, the two auctions that differ only in the information on previous dropouts. Both rational and behavioral benchmarks predict that additional information improves bidders' precision in estimating the value. This prediction, however, is not borne out in our data. Figure 4 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.[37]

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

[37] We 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.

Figure 4: Squared distance to common value



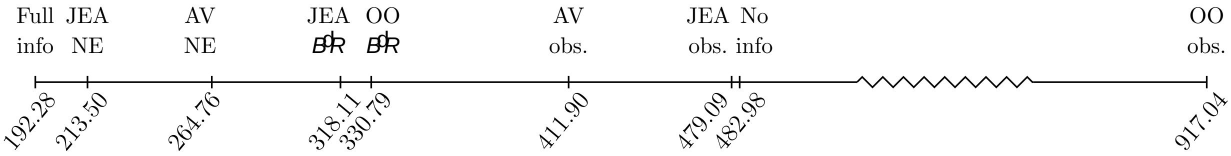

rational bidder would (*information processing*). To isolate the two forces, we use an empirical best response $\widehat{BR}$ as described in Section 6.2, given observed bidding behavior of early dropouts.

Note that $\widehat{BR}$ is a statistic that separates between information processing and revelation. It represents the level at which the two remaining 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.

Using the empirical best response, we can also provide a lower bound for the importance of heterogeneity in early dropouts on the failure of information aggregation. Using bidder fixed effects, instead of only session fixed effects, when estimating signals from observed bids, the squared distance of the empirical best response to the common value reduces to 303.0. The difference of this new benchmark to the empirical best response is significant (Wilcoxon signed-rank test, 10 observations, p-value=0.047). Note that this is a lower bound due to the role played by individual heterogeneity, as it ignores the additional gains brought about by bidders iteratively making the intermediate dropouts more precise, something they cannot do as the identity of other bidders is not observed.

Lastly, when it comes to our third auction format, the OO, the higher revenue that we observe is not caused by a higher degree of information aggregation in this 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 5 presents the information aggregation benchmarks of the OO in comparison to the other auction formats.

Figure 5: Squared distance to common value, including the OO




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

We have previously seen that revenue is higher in the OO than in the other two formats. Also, information 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, beyond the average revenue already being significantly higher, we also observe relatively many extreme auction revenues in the OO compared to the other two formats. 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.[38] 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)[39], thus when becoming active and winning an auction, bidders with strong endowment effects lose more money. This evidence provides support for the conjecture that the OO activates auction fever among people who suffer from the endowment effect.

A second important feature of the OO is that bidders can submit non-incremental jump bids. Theoretical analyses of jump bidding suggest that this may be a profitable strategy for a jump-bidder. Avery (1998) derives equilibria in which jump bidding is used for signaling high value estimates, which predicts increased profits for the winner. Ettinger and Michelucci (2016) show that jump bidding can be used to obfuscate information. Naturally, behavioral factors may also affect jump bidding. For example, impatient bidders who are determined to win an auction quickly might frequently submit jump bids which lead them to win auctions in cases in which they have initially overestimated the value, an error which could have been corrected in the price discovery of an incremental bidding process. These behavioral factors suggest that jump bidding may also be costly and reduce winners' profits. In the following, we evaluate the effect of jump bidding in the OO auctions, focusing on whether jump bidding increases 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 stand-

[38] We 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).

[39] This analysis is robust to performing a median split based on the first principal component obtained from the two measures of the endowment effect, with $p$-values of .564 and .083, respectively (MWU-tests, 8 observations).

ing 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 construct the total jump bid of each bidder in each round. To do so, we first calculate 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, this increment varies 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 increments for one bidder across one auction as the total jump bid of this bidder.

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.[40]

In Table 6, 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, in regressions studying the effect of jump bids, these bids are likely endogenous as strategies adjust to observed jump bids submitted earlier. To account for this, we rely on instruments generated from other rounds, which capture an individual bidder's proneness for jump bidding. As instruments, we use the average total jump bid of each bidder across all other rounds, as well as the maximum bid increment in any of the other rounds. Using 2SLS, we then predict in a first stage the total jump bid in the current round using the two instruments and other variables, such as the signal $x$. In the second stage, we regress our dependent variables of interest on the predicted total jump

[40]In 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 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.

bid and some other variables. This provides a clean identification of the effect of jump bids. For relevance, we here assume that a bidder's proneness to jump bid in other rounds correlates with this bidder's jump bidding in the particular round. For the exclusion restriction, we assume that other rounds' jump bids only affect outcomes through the bidding in that particular round. We think that this is plausible for two reasons. First, the only way of affecting a particular round's outcomes is only through bidding in that round, while other rounds' bids (our instruments) cannot directly affect outcomes by the auction rules. Second, as for potential indirect effects, this exclusion is reinforced by our experimental design, as every round bidders draw new random signals and are allocated to new random groups within the matching group, which limits the effects other rounds' behavior may have on this round's competitors. In the Appendix Section A.11, we present first-stage regression results in combination with a robustness check based on the use of only the average total jump bids across all other rounds as instrument. We show that the instruments are relevant, as all first stage regressions are significant at conventional levels, with Kleibergen-Paap $F$-statistics of 96.4 or greater. In addition, we show that we cannot reject the null hypothesis that the instruments are valid, with $p$-values of the Hansen J-statistic of .582 or higher.

Column (1) presents results of regressing these jump bids on bidders' information. As predicted by theoretical models, bidders with higher signals submit higher jump bids. The size of the jump bid is not significantly increasing over time. Interestingly, this suggests that bidders with more experience shift their jump bids to the start of the auction, as we do observe a significant increase in jump bidding at the start over time while overall jump bidding remains constant.[41]

Table 6 also presents an analysis of the effects of jump bids. In (2), the dependent variable is a dummy equal to one when a bidder wins the auction, 0 otherwise. Here we show that, controlling for own signal, a larger jump bid increases the likelihood to win the 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. Contrary to theoretical predictions, profits are significantly decreasing in the size of the jump.

Winners on average lose money in the OO and, by submitting a jump bid,

[41]In the last 4 sessions, we elicited how much participants agreed with several motives for jump bidding in the questionnaire, see Appendix Section A.12 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."

Table 6: Effect of jump bids in the OO

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Jump bid | Pr(win) | Profits | Winners' profits |
| Total jump bid (IV) | | 0.350 | -0.261 | -0.316 |
| | | (0.083) | (0.115) | (0.133) |
| $x$ | 0.276 | 0.144 | -0.067 | -0.029 |
| | (0.031) | (0.038) | (0.037) | (0.042) |
| $t$ | -0.138 | | 0.877 | 0.784 |
| | (0.124) | | (0.169) | (0.154) |
| $V$ | | | 0.624 | 0.633 |
| | | | (0.046) | (0.064) |
| Constant | 30.433 | -12.306 | -66.653 | -58.996 |
| | (5.897) | (2.656) | (7.000) | (9.917) |
| Observations | 2687 | 2687 | 2687 | 600 |
| Adjusted $R^2$ | 0.070 | 0.102 | 0.291 | 0.287 |
| 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 total jump bid on bidders' signals and round $t$. In (2) to (4), we use 2SLS, where we instrument using the average total jump bid and the maximum bid increment in other rounds. (2) is the ex-post probability of winning, which is a dummy equal to 100 if a bidder wins the auction, 0 otherwise. Mean earnings are a participants' average earning across all auctions, winners' pro ts are the earnings for the auctions which a participant won. $x$ is the submitting bidder's signal in round $t$. $V$ represents the common value. Standard errors in parentheses, clustered at the matching group level.

participants select into this group of winners making a loss. Model (4) studies whether this selection effect is the full reason beyond the negative relation between jump bidding and profits. We do so by restricting the analysis to bidders who end up winning the auction. We find that even within this group of bidders, the size of the jump bid decreases profits further.

Results for experienced bidders are similar, see Table 14 in the Appendix. In later rounds, jump bidding has a slightly less pronounced effect on earnings and profits. Still, jump bidding continues to be a disadvantageous strategy also 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 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 and the AV both raise higher revenue than expected in the symmetric Nash equilibrium. In contradiction to some behavioral models that predict higher revenue for the AV, we do not reject equality of revenue between the JEA and 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 more strongly with the most recent dropout than in the AV benchmark.[42] The bidding pattern, however, deviates from what would be observed when bidders bid according to the Nash equilibrium benchmark, and also from what would be observed when they choose empirical best responses. 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

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

sufficiently to tamper 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 heterogeneity in the bidding of early leavers. In agreement with the fact that it is relatively cheap to drive up the price in the JEA, spiteful bidders may stay longer in the JEA than in the AV, forcing cooperators to stay longer in the cases where they want to win. Such spiteful bidding by early leavers may neutralize 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 is the worst approximation of the common value 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 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 Online Appendix to "Why are open ascending auctions popular?"

The Appendix is intended for online publication. We start with an analysis of information effects on eBay. Then, we discuss revenue predictions for different parameterizations, and we present behavioral models. 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.

## 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 6, 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

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

(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.[44]

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, 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.

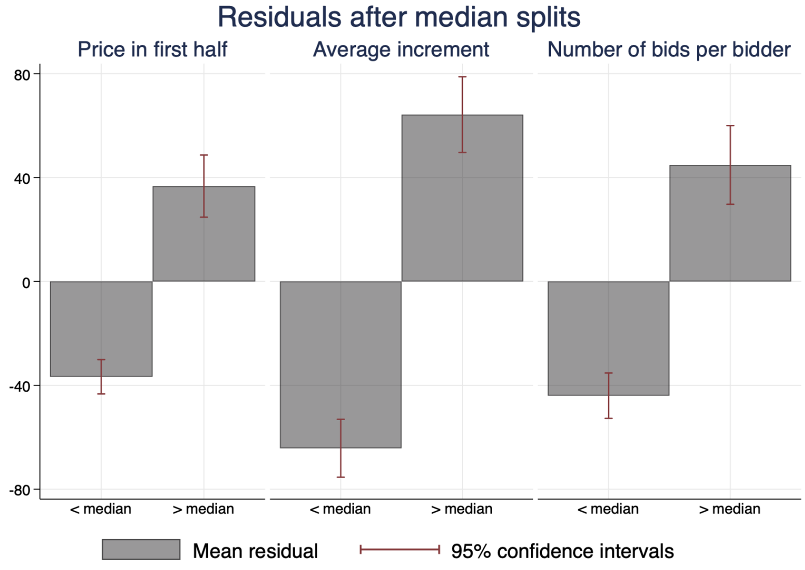
Crucially, this type of observational data cannot be used to establish unambiguously that information revelation is taking place and what effect revealing information has. First of all, the direction of causality is not clear (e.g., are expensive phones attracting many bids, or do many bids increase 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 7, 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 7, $R_{AV}$ 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 $\mu$ and standard deviation $\sigma_V$ of the value distribution as well as the standard deviation $\sigma_\epsilon$ 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

[44]As we perform the median split on these characteristics, we do not residualize the reserve price when performing the split on the price in the first half, and we do not residualize the number of bids and the number of bidders when performing the split on the number of bids per bidder.

Figure 6: Residuals obtained from regressions of final price




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.

Additionally, we calculated revenue differences for varying numbers of bidders. In Table 8, for the paramaterization used in this experiment, $(\ ;\ _{v};\ ) = (100; 25; 35)$, 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 Nash predictions with varying parameters

| $( \; ; \; _V ; \; )$ | | $R_{AV}$ | $R_{JEA}$ |
|---|---|---|---|
| (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) |

Table 8: Revenue predictions varying number of bidders, $( \; ; \; _V ; \; ) = (100; 25; 35)$

| 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:

$$b(x_i) = x_i$$

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 (2003$b$):[45]

$$b(x_i) = \mathrm{E}[V|x_i] = x_i \quad \mathrm{E}[\ _i|x_i]$$

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.

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 $\mathbf{Y}_i$, this implies the following bid:

$$b_j(x_i; \mathbf{Y}_i) = \frac{1}{j} x_i + \frac{1}{j} \sum_{k=1}^{j\ \ 1} Y_{i;(k)}$$

This formulation can be rewritten to only depend on the last dropout price, for the vector of previous dropout prices $\mathbf{p}_{j\ \ 1}$, $p_{j\ \ 1}$ being the $j\ \ 1$-th observed dropout:

$$b_j(x_i; \mathbf{p}_{j\ \ 1}) = x_i + \frac{j\ \ 1}{j} p_{j\ \ 1}$$

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.

[45]Within the setup of our experiment, we can use that $\ _i|x_i \quad N\left(\frac{^2(x_i\quad)}{^2+\ _V^2}; \frac{^2\ _V^2}{^2+\ _V^2}\right)$. As derived in Goeree and Offerman (2003$b$): $b(x_i) = \frac{_V^2 x_i + \ ^2}{_V^2 + \ ^2}$

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 $p_{j \ 1}$ being the $j \quad$ 1-th dropout, bids are given by:

$$b_j(x_i; \mathbf{p}_{j \ 1}) = \frac{1}{j} x_i + \frac{1}{j} \sum_{k=1}^{j \ 1} p_k$$

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 $j \quad 1$ observed dropouts, bidder $i$ calculates the average of available signals $\bar{x}_i = \frac{1}{j} x_i + \frac{1}{j} \sum_{k=1}^{k \ 1} Y_{i;(5 \ k)}$:

$$b(\bar{x}_i) = \frac{\ ^2_V \bar{x}_i + \ \ ^2}{\ ^2_V + \ \ ^2}$$

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.

## A.4 Cursed equilibrium in the JEA

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

$$(V; p) = (1 \qquad )V + \quad \mathrm{E}[V | X_i = x_i] \quad p$$

for price $p$, compared to winners' payoff in Nash equilibrium of $(V; p) = V \quad p$. We continue to analyze a game where 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

$$b_j(x_i) = \mathrm{E} \ V | X_i = x_i; Y_{i;(1)} = x_i; \ldots; Y_{i;(5 \ j)} = x_i; p_1 = b_1 \ Y_{i;(4)} \ ; \ldots$$
$$\ldots; p_{j \ 1} = b_{j \ 1} \ Y_{i;(5 \ j+1)}$$

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

$$E\Big[(1 \quad )V + \quad E[V|X_i = x_i] \;\Big|\; X_i = x_i; Y_{i;(1)} = x_i; \dots; Y_{i;(5 \; j \; 1)} = x_i; p_1 = b_1 \; Y_{i;(4)} \; ; \dots$$

$$\dots; p_{j \; 1} = b_{j \; 1} \; Y_{i;(5 \; j+1)} \Big]$$

$$= (1 \quad )E[V|X_i = x_i; Y_{i;(1)} = x_i; \dots; Y_{i;(5 \; j \; 1)} = x_i; p_1 = b_1 \; Y_{i;(4)} \; ; \dots; p_{j \; 1} = b_{j \; 1} \; Y_{i;(5 \; j+1)} \;]$$

$$+ \quad E[V|X_i = x_i]$$

As Milgrom and Weber (1982) have shown that $b_j(x_i)$ is a Nash equilibrium in the original game, the expression above is a symmetric cursed equilibrium in a -virtual game, for $\; 2 \; [0;1]$.

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

We estimate for the AV:

$$b(x_i) = \underbrace{x_i \quad \left( \frac{\int_1^1 {}_V(x_i \quad ) \; {}^2(\;)\Phi^3(\;)\,d}{\int_1^1 {}_V(x_i \quad ) \; {}^2(\;)\Phi^3(\;)\,d} \right)}_{=w_i} +$$

$$+ \quad \underbrace{\left( \frac{{}^2 x_i + \quad {}^2}{{}^2_V + \quad {}^2} + \frac{\int_1^1 {}_V(x_i \quad ) \; {}^2(\;)\Phi^3(\;)\,d}{\int_1^1 {}_V(x_i \quad ) \; {}^2(\;)\Phi^3(\;)\,d} \right)}_{=z_i}$$

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

$$b(x_i) = \;_1 w_i + \;_2 z_i$$

In a constrained regression, we impose no constant and $_1 = 1$. Then, $_2 =$ .

For the JEA, we proceed similarly. We first simulate Nash equilibrium bids, based on the inference of observed dropouts.[46] We also use OLS to estimate in the following equation:

$$b_k(x_i; \bar{x}_i) = \underbrace{\frac{5\bar{x}_i \; {}^2_V + \quad {}^2}{5 \; {}^2_V + \quad {}^2}}_{=w_i} + \underbrace{\frac{{}^2_V x_i + \quad {}^2}{{}^2_V + \quad {}^2} \quad \frac{5\bar{x}_i \; {}^2_V + \quad {}^2}{5 \; {}^2_V + \quad {}^2}}_{=z_i}$$

We regress dropout prices on $x_1; x_2$:

$$b_k(x_i; \bar{x}_i) = \;_1 w_i + \;_2 z_i$$

Again using constrained regression with no constant and $_1 = 1$, we obtain $_2 =$ .

[46]Note 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.

In Table 9, we summarize the regression results. We estimate   once for all pooled data and once for the fourth dropouts in (2) and (4), respectively.

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

Table 9: Estimating

| | (1) AV | (2) AV, $d_4$ | (3) JEA | (4) JEA, $d_4$ |
|---|---|---|---|---|
| $w_i$ | 1.000 | 1.000 | 1.000 | 1.000 |
| | (.) | (.) | (.) | (.) |
| $z_i$ (for ˆ) | 0.058 | 0.985 | -0.137 | 0.186 |
| | (0.058) | (0.072) | (0.059) | (0.041) |
| Observations | 2417 | 598 | 2453 | 599 |
| Estimation | OLS | OLS | OLS | OLS |

*Notes:* Standard errors in parentheses and clustered at the matching group level.

## A.5 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 $_{i;t;m}$ the distance of the bid by bidder $i$ in round $t$, compared to model $m$. $b_{j;i;t}$ is the observed dropout price of bidder $i$ in round $t$, dropping out at order $j$.[47] $b^m_{j;i;t}$ is the theoretically predicted dropout price by model $m$ for this bid. The distance $_{i;t;m}$ is given by:

$$_{i;t;m} = \quad b_{j;i;t} \quad b^m_{j;i;t} \quad ^2$$

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.[48] For this, we run regressions which use the identical available infor-

[47] Here, we only consider bidders who actively choose to drop out.

[48] Note that all models are in fact linear models. Derivations are available on request.

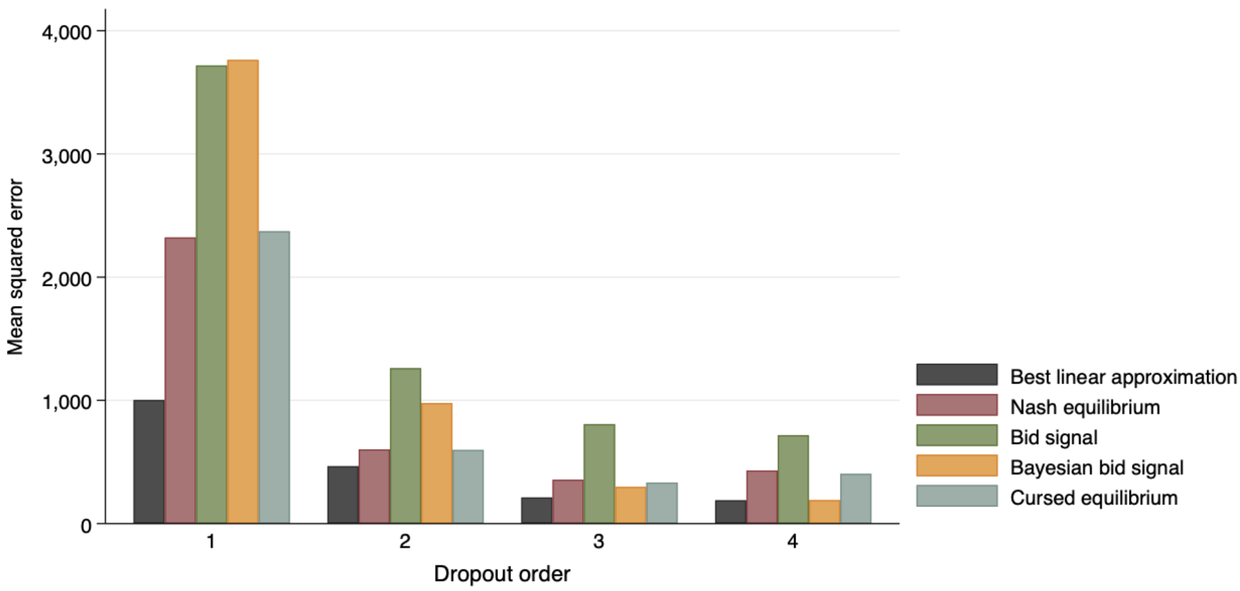
mation as the models, which is the bidder's signal and dropouts in case they are observable. We then state the mean squared error of this prediction. By design, this minimizes this error within the class of linear models, which nests all models which are competing in this analysis.

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 dropout order is the most interesting, as these determine 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 (2003*b*), and iii) bidders in cursed equilibrium as proposed by Eyster and Rabin (2005), with an estimated ˆ = :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 7: Mean squared error of model predictions in the AV

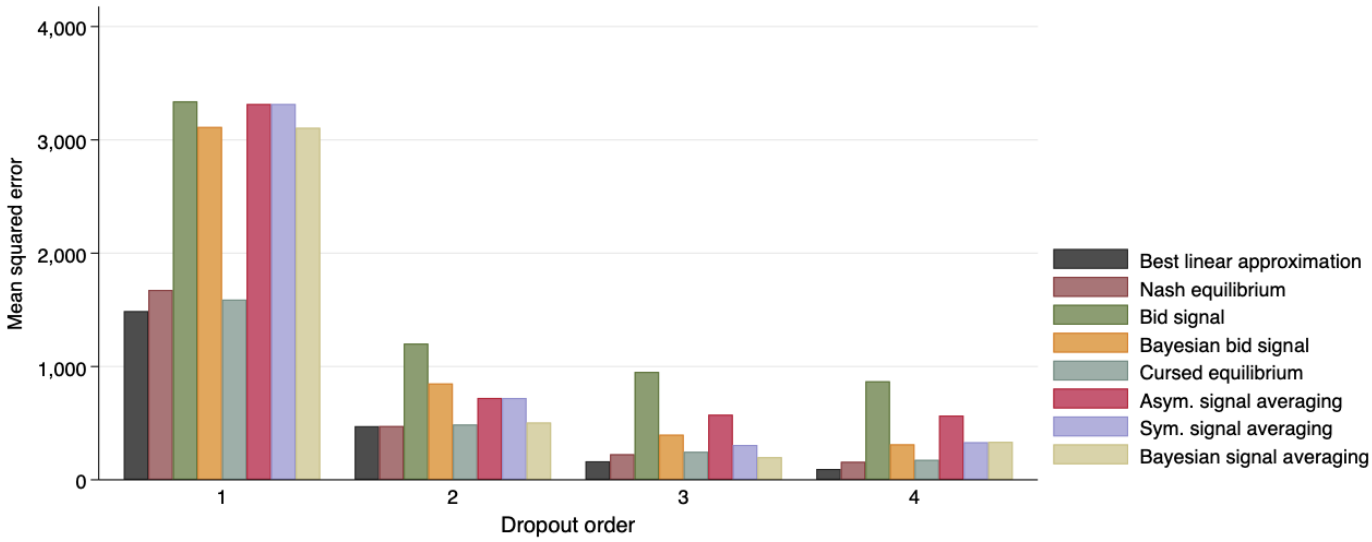



The first key insight is the fact that bidding behavior at early dropout orders is substantially less well predicted, as the mean squared error of the benchmark is much larger for early dropout orders than for late dropout orders. This decrease in the error in dropout orders also holds for most other 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.[49] 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 8: 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

[49] For this auction format, we estimate $\hat{} = \ 0{:}137$.

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 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.[50] 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.

### A.5.1 Bid classification tables

Table 10 reports distances to predictions based on observed bidding.

[50] Note 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 10: Classifying bids into models

| | AV | JEA | | AV | JEA |
|---|---|---|---|---|---|
| | First dropout | | | Third dropout | |
| Nash | **2321.8** | *1675.4* | 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 |
| cursed | *2372.2* | **1590.5** | 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 | *602.3* | **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 |
| cursed | **597.6** | *488.2* | cursed | 404.0 | *176.4* |
| 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 |

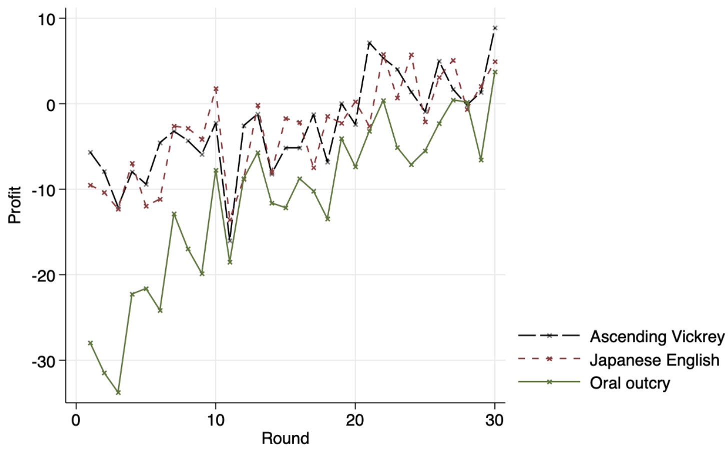
*Note:* Average distance of observed bids to all considered models, by auction format and dropout order. Distances are squared distance from observed bid to bid predicted by each model. The best tting model's distance is in bold, models within 10% of the best model's t are italicized.

## A.6 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 9, we plot the evolution of the winning bidders' profits over rounds, by auction format.

Figure 9: 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.

## A.7 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 11 repeats this anaylsis for rounds 16-30.

Table 11: Bidders' use of information in JEA

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | $b_1$ | $b_2$ | $b_3$ | $b_4$ | | | | $V$ | $BR$ |
| | Observed | Observed | Observed | Observed | Nash | SA | BSA | | |
| $x$ | 0.329 | 0.274 | 0.179 | 0.149 | 0.287 | 0.250 | 0.168 | 0.232 | 0.290 |
| | (0.078) | (0.057) | (0.047) | (0.035) | (0.000) | (0.000) | (0.000) | (0.040) | (0.001) |
| $b_1$ | | 0.341 | 0.038 | 0.029 | 0.100 | 0 | 0 | -0.010 | 0.017 |
| | | (0.063) | (0.026) | (0.015) | (.) | (.) | (.) | (0.035) | (0.005) |
| $b_2$ | | | 0.537 | -0.010 | 0.167 | 0 | 0 | -0.011 | 0.047 |
| | | | (0.089) | (0.019) | (.) | (.) | (.) | (0.057) | (0.008) |
| $b_3$ | | | | 0.641 | 0.333 | 0.750 | 0.832 | 0.302 | 0.143 |
| | | | | (0.088) | (.) | (.) | (.) | (0.085) | (0.009) |
| $t$ | -0.592 | 0.201 | 0.288 | -0.063 | | | | 0.379 | -0.041 |
| | (0.522) | (0.423) | (0.163) | (0.140) | | | | (0.187) | (0.007) |
| Constant | 35.745 | 34.694 | 23.235 | 26.580 | 11.265 | 0 | 0 | 41.700 | 50.207 |
| | (17.143) | (10.104) | (5.317) | (4.495) | (.) | (.) | (.) | (6.651) | (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:* $b_j$: dropout price at order $j$; $V$: common value; $x$: own signal. (1) to (4) are xed e ects estimates (within estimation) of information use. Dependent variables (in columns) are dropout prices at each order, e.g. (1) are all bidders dropping out rst in an auction. Regressors (in rows) are the available information at each dropout order, i.e., the signal $x$ and the preceding dropout prices $\mathbf{b}_{j-1}$. (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-speci c absorbing indicators. The latter also includes t obtained from subject xed e ects. Standard errors in parentheses, clustered at the matching group level.

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 show that bids are more strongly correlated in the JEA than in the AV. Table 12 repeats this analysis for rounds 16-30. Results are in line with results in the full data set, apart from the coefficient on the interaction term of $b_1$ and JEA in the regression of $b_2$.

Table 12: Comparing information use in the AV and the JEA, round 16-30

| | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|
| $b_{j-1}$ | 0.316<br>(0.050) | 0.268<br>(0.026) | 0.325<br>(0.039) |
| JEA $b_{j-1}$ | 0.026<br>(0.079) | 0.269<br>(0.091) | 0.316<br>(0.094) |
| Observations | 599 | 599 | 599 |
| Adjusted $R^2$ | 0.432 | 0.733 | 0.784 |

*Notes:* $b_{j-1}$ denotes the just preceding dropout, e.g. is $b_1$ for $b_2$. JEA is a dummy equal one for JEA auctions. Other variables in regression omitted from table: all regressions include signal $x$, round $t$, all preceding dropouts ($b_{j-k}$ for all $k \in \{1, \ldots, j-1\}$), as well as all these variables interacted with the JEA-dummy and a constant. Standard errors in parentheses and clustered at the matching group level.

In Table 5, we study whether separately elicited characteristics of subjects correlate with the fixed effect we estimate from bidders' information use. Table 13 repeats this with experienced bidders.

Point estimates are mostly comparable to the analysis with the full data set in the main text. There are some estimates with larger standard errors, e.g. Imitator is no longer significant in (1). Point estimates for Imitator in the JEA in (2) turn negative, but remain not significant. The coefficient on SVO in the AV in (3) and the JEA in (4) turns positive and significant, comparable to the coefficient for early bids in (1). 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 $b_1$ & $b_2$, as well as for five bidders for $b_3$ & $b_4$, we cannot obtain a fixed effect any longer, as we don't have observations at these dropout orders for these bidders.

In Figure 5 in the main text we plot squared distances from the value to the prices in the auction and to some benchmarks, respectively. In Figure 10, 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,

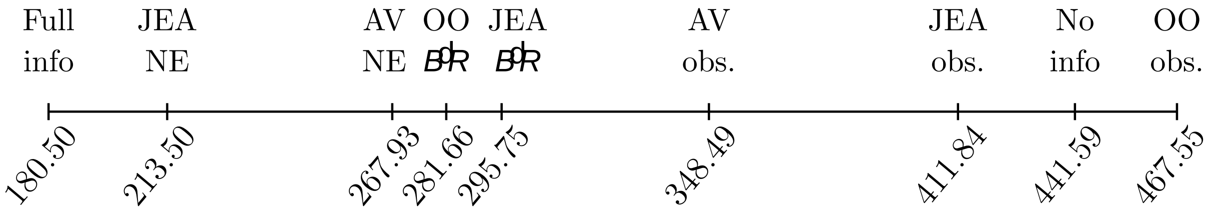
Table 13: Bidder fixed effects and their characteristics, rounds 16 to 30

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Average bidder fixed effect | | | |
| | $b_1$ & $b_2$ | | $b_3$ & $b_4$ | |
| | AV | JEA | AV | JEA |
| SVO | 0.110 | -0.222 | 0.100 | 0.117 |
| | (0.043) | (0.213) | (0.034) | (0.030) |
| Imitator | 4.469 | -1.086 | 3.014 | 3.179 |
| | (3.668) | (7.912) | (2.023) | (2.032) |
| Constant | 0.894 | 7.993 | -4.797 | -3.264 |
| | (1.847) | (3.317) | (1.295) | (1.949) |
| Observations | 50 | 39 | 47 | 38 |
| Adjusted $R^2$ | -0.006 | -0.013 | 0.035 | 0.141 |

*Notes:* Average xed e ects from regressing bids on available information for rst and second vs. third and fourth dropout. 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.

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 10: Squared distance to common value, rounds 16 to 30




In Table 6 in the main text, we investigate the effect of jump bids. In Table 14, we repeat this analysis for rounds 16 to 30, also constructing instruments only from experienced bids. Effects of jump bidding appear to be somewhat less pronounced in the second half of the data, but broadly similar.

Table 14: Effect of jump bids in the OO, rounds 16-30

| | (1) Jump bid | (2) Pr(win) | (3) Profits | (4) Winners' profits |
|---|---|---|---|---|
| Total jump bid (IV) | | 0.341 | -0.106 | -0.232 |
| | | (0.097) | (0.054) | (0.067) |
| $x$ | 0.283 | 0.178 | -0.118 | -0.095 |
| | (0.029) | (0.043) | (0.014) | (0.025) |
| $t$ | -0.043 | | 0.471 | 0.434 |
| | (0.185) | | (0.130) | (0.175) |
| $V$ | | | 0.587 | 0.630 |
| | | | (0.059) | (0.071) |
| Constant | 27.738 | -14.532 | -57.356 | -49.753 |
| | (7.274) | (2.465) | (4.318) | (8.201) |
| Observations | 1309 | 1309 | 1309 | 300 |
| Adjusted $R^2$ | 0.072 | 0.097 | 0.304 | 0.283 |
| Estimation | OLS | 2SLS | 2SLS | 2SLS |
| First-stage F-statistic | | 490.25 | 500.05 | 188.05 |
| Hansen J-statistic, p-value | | .800 | .249 | .620 |

*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 bids and the maximum bid increment in other rounds. $x$ is the submitting bidder's signal in round $t$. $V$ represents the common value. Standard errors in parentheses, clustered at the matching group level.

## A.8 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 15 shows results of regressing signals on bids, which we in turn use to predict signals based on observable bids, where $x_j$ refers to the signal of the bidder dropping out in $j$-th order in round $t$, and $\hat{x}_j$ refers to the predicted signal of the bidder dropping out in $j$-th order.

In Table 4, we show that bids are more strongly correlated in the JEA than in the AV, suggesting that information is actively used in the open format. Doing so controls for the correlation of unobservable dropouts in the AV, which arise as in these regressions bids are ordered. Table 16 shows the full regression results.

Table 15: Predicting signals with observed bids

| | (1) | (2) | (3) |
|---|---|---|---|
| | $x_1$ | $x_2$ | $x_3$ |
| $d_j$ | 0.205 | 0.567 | 1.009 |
| | (0.064) | (0.089) | (0.087) |
| $x_1$ | | 0.048 | 0.081 |
| | | (0.191) | (0.226) |
| $x_2$ | | | -0.147 |
| | | | (0.140) |
| $t$ | 0.270 | 0.177 | 0.166 |
| | (0.202) | (0.175) | (0.140) |
| Constant | 68.089 | 33.977 | 5.797 |
| | (4.111) | (11.964) | (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.

Table 16: Comparing information use in the AV and the JEA

| | | $b_1$ | $b_2$ | $b_3$ | $b_4$ |
|---|---|---|---|---|---|
| $x$ | | 0.247 | 0.297 | 0.242 | 0.227 |
| | | (0.0457) | (0.0216) | (0.0224) | (0.0298) |
| $b_1$ | | | 0.285 | -0.00113 | -0.0141 |
| | | | (0.0309) | (0.0172) | (0.0209) |
| $b_2$ | | | | 0.357 | -0.0114 |
| | | | | (0.0319) | (0.0317) |
| $b_3$ | | | | | 0.465 |
| | | | | | (0.0440) |
| $t$ | | -0.498 | -0.0381 | -0.126 | -0.174 |
| | | (0.155) | (0.0872) | (0.0596) | (0.0341) |
| JEA | $x$ | 0.0464 | -0.0296 | -0.0704 | -0.109 |
| | | (0.0718) | (0.0398) | (0.0342) | (0.0336) |
| JEA | $b_1$ | | 0.0871 | 0.0244 | 0.0392 |
| | | | (0.0463) | (0.0243) | (0.0253) |
| JEA | $b_2$ | | | 0.195 | -0.0271 |
| | | | | (0.0533) | (0.0479) |
| JEA | $b_3$ | | | | 0.244 |
| | | | | | (0.0827) |
| JEA | $t$ | 0.181 | -0.0844 | 0.0433 | 0.0991 |
| | | (0.315) | (0.141) | (0.0937) | (0.0455) |
| Constant | | 32.09 | 38.94 | 37.14 | 33.30 |
| | | (4.573) | (1.653) | (1.969) | (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.

## A.9 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 17: Residual estimations

| | $b_1$ | $b_2$ | $b_3$ |
|---|---|---|---|
| $b_1$ | | 0.477 | 0.0221 |
| | | (0.0385) | (0.00955) |
| $b_2$ | | | 0.665 |
| | | | (0.0435) |
| $t$ | -0.555 | -0.148 | -0.0479 |
| | (0.318) | (0.108) | (0.0949) |
| Constant | 77.19 | 60.20 | 36.93 |
| | (4.930) | (2.747) | (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.

We then regress dropouts at later dropout orders on these residuals, results are reported in Table 18. 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.[51]

In (1) to (3), we observe that the effect of a bidder's private information, captured by $x$ 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 $e_1$). Similarly, bidders' private information, $x$, is weighted less than in the benchmarks.

[51] In 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 18: Information effects captured by residuals

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Observed | | | Nash equilibrium | | | Bayesian signal-averaging | | |
| | $b_2$ | $b_3$ | $b_4$ | $b_2$ | $b_3$ | $b_4$ | $b_2$ | $b_3$ | $b_4$ |
| $x$ | 0.272 | 0.168 | 0.120 | 0.575 | 0.431 | 0.287 | 0.253 | 0.202 | 0.168 |
| | (0.0220) | (0.0211) | (0.0180) | (0.00000261) | (0.00000411) | (0.00000549) | (0.00000220) | (0.00000475) | (0.00000568) |
| $e_1$ | 0.401 | 0.286 | 0.250 | 0.200 | 0.354 | 0.491 | 0.747 | 1.057 | 1.220 |
| | (0.0392) | (0.0186) | (0.0134) | (0.00000342) | (0.00000524) | (0.00000515) | (0.00000366) | (0.0000154) | (0.0000112) |
| $e_2$ | | 0.566 | 0.429 | | 0.250 | 0.458 | | 0.798 | 1.218 |
| | | (0.0455) | (0.0328) | | (0.0000102) | (0.00000744) | | (0.0000198) | (0.0000204) |
| $e_3$ | | | 0.719 | | | 0.333 | | | 0.832 |
| | | | (0.0710) | | | (0.0000234) | | | (0.0000370) |
| Constant | 60.04 | 78.92 | 90.86 | 37.08 | 49.18 | 63.64 | 65.16 | 69.01 | 74.32 |
| | (2.940) | (2.711) | (2.151) | (0.000190) | (0.000386) | (0.000619) | (0.000157) | (0.000484) | (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.

## A.10 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 19.

Table 19: Bidder fixed effects and their characteristics

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Average bidder fixed effect | | | |
| | $b_1$ & $b_2$ | | $b_3$ & $b_4$ | |
| | AV | JEA | AV | JEA |
| SVO | 0.118 | -0.231 | 0.037 | 0.045 |
| | (0.024) | (0.037) | (0.024) | (0.037) |
| Imitator | 5.364 | 4.840 | 5.606 | 1.080 |
| | (1.030) | (1.695) | (1.030) | (1.695) |
| Constant | 0.492 | 7.681 | -3.719 | -0.615 |
| | (0.716) | (1.092) | (0.716) | (1.092) |
| Observations | 50 | 40 | 50 | 40 |
| Estimation | WLS | WLS | WLS | WLS |

*Notes:* Average xed e ects from regressing bids on available information for rst 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 xed e ect, averaged at $d_1$ and $d_2$, and at $d_3$ and $d_4$. Standard errors in parentheses.

We observe that the point estimates presented in the main text carry over. In addition, some coefficients which are not significant in the main text are highly significant in this specification, e.g. the coefficient on SVO in JEA in (2).

## A.11 Further results on jump bidding

In the main text, we report 2SLS estimations, where we instrument for the total jump bid with the maximum bid increment and average total jump bid of each bidder obtained in all other rounds.

In Table 20, we report results of the first stage. In addition, we report the Kleibergen-Paap F-statistic, which suggests that the instruments are relevant, and $p$-values for the Hansen J-statistic, which do not reject that the chosen instruments are valid. Columns (2), (3) and (4) show first-stage results for each of the corresponding second-stages in Table 6 in the main text.

Table 20: First stage for 2SLS estimation

| | (2) | (3) | (4) |
|---|---|---|---|
| | Dependent variable: total jump bid | | |
| Maximum increment in other rounds | 0.163 | 0.163 | 0.151 |
| | (0.032) | (0.032) | (0.060) |
| Mean total jump bid in other rounds | 0.582 | 0.584 | 0.699 |
| | (0.069) | (0.071) | (0.079) |
| $x$ | 0.279 | 0.302 | 0.175 |
| | (0.028) | (0.029) | (0.046) |
| $V$ | | -0.076 | 0.106 |
| | | (0.018) | (0.046) |
| $t$ | | -0.163 | -0.528 |
| | | (0.122) | (0.201) |
| Constant | -26.761 | -19.123 | -9.381 |
| | (5.742) | (7.061) | (8.876) |
| Observations | 2687 | 2687 | 600 |
| F-statistic | 96.4 | 98.7 | 143.3 |
| Hansen J-test | .584 | .582 | .948 |

*Notes:* The dependent variable across all rst-stage regressions is the total jump bid, given by the sum of bid increments beyond the current price within a round. As instruments, we use the maximum bid increment and the mean total jump bid for each bidder in all but the current round. $x$ is the submitting bidder's signal in round $t$. $V$ represents the common value. Standard errors in parentheses, clustered at the matching group level.

For robustness, we repeat the analysis in Table 6 using only the mean total jump bid in other rounds, and show results in Table 21.

Table 21: Effect of jump bids in the OO, one instrument

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Jump bid | Pr(win) | Pro ts | Winners' pro ts |
| Total jump bid (IV) | | 0.343 | -0.274 | -0.315 |
| | | (0.087) | (0.134) | (0.151) |
| *x* | 0.274 | 0.146 | -0.064 | -0.031 |
| | (0.032) | (0.039) | (0.043) | (0.044) |
| *t* | -0.137 | | 0.875 | 0.779 |
| | (0.125) | | (0.166) | (0.151) |
| *V* | | | 0.624 | 0.634 |
| | | | (0.046) | (0.066) |
| Constant | 30.525 | -12.128 | -66.217 | -58.989 |
| | (5.937) | (2.756) | (6.987) | (10.231) |
| Observations | 2687 | 2687 | 2687 | 600 |
| Adjusted $R^2$ | 0.069 | 0.103 | 0.284 | 0.286 |
| Estimation | OLS | 2SLS | 2SLS | 2SLS |
| F-statistic | | 86.9 | 85.7 | 325.2 |

*Notes:* Jump bid is the increment of a bid beyond the current price at the moment the bid was submitted. In (1), we regress total jump bid on bidders' signals and round *t*. In (2) to (4), we use 2SLS, where we instrument using the average total jump bid in other rounds. (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' pro ts are the earnings for the auctions which a participant won. *x* is the submitting bidder's signal in round *t*. *V* represents the common value. Standard errors in parentheses, clustered at the matching group level.

## A.12 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.

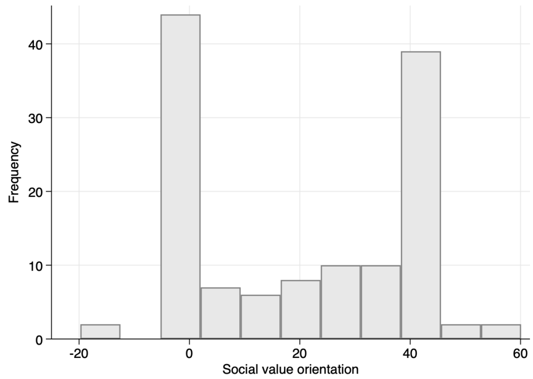
Below is the mean and standard deviation of how much people agree with a given statement. The scale is from 1 to 7, where 7 is fully agreeing, 4 is undecided.

| 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 |

### A.13 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 11 gives a histogram of observed choices.

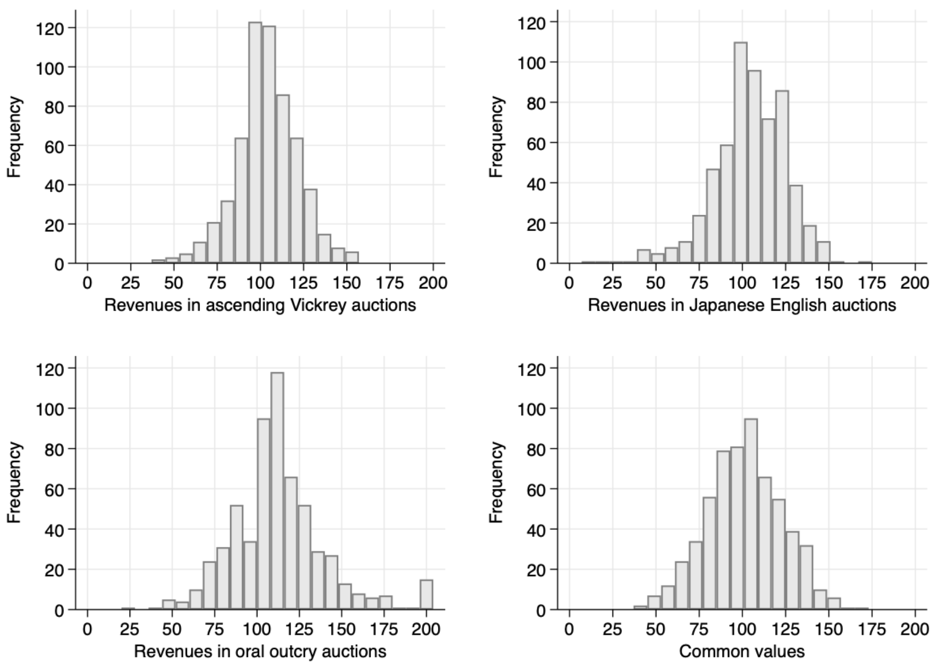
Figure 11: Angle in circle test




## A.14 Histograms of auction revenues

In Figure 12, we plot histograms of the revenues in all three auction formats as well as a histogram of the common values drawn.

Figure 12: Histograms of the drawn common values and revenues.



# B 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.

## B.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.

*f*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.

*f*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.*gf*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.*g*

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.*g*

*f*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.

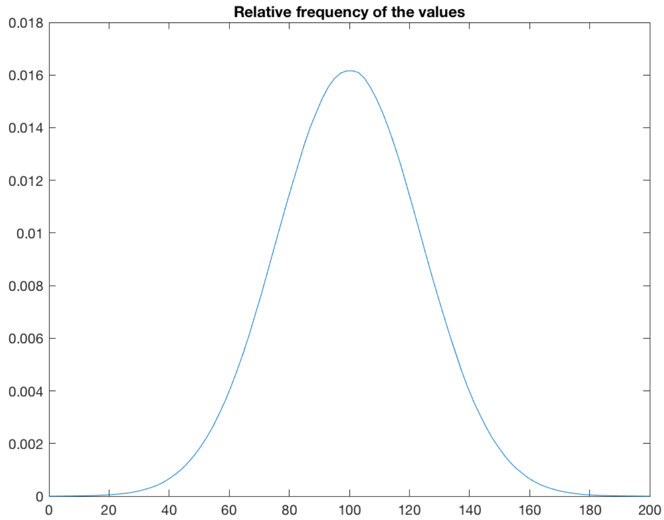
At the end of each period, so when a countdown elapses before any new bid is submitted, the earnings of the bidders are calculated as follows: The winner of the auction is the bidder who submitted the highest maximum bid, and he or she will pay a price equal to the CURRENT PRICE when bidding stopped. 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.*g*

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**

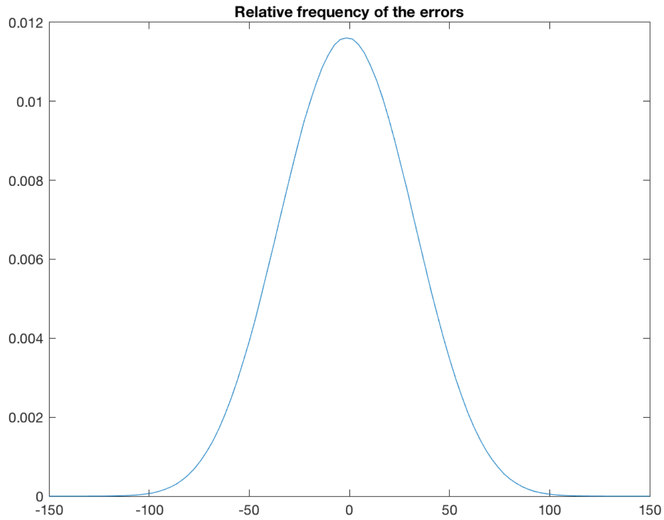
The value of the product is a random number which changes in each period. You cannot learn anything about subsequent value draws from previously observed values. Within the period the value is identical for all participants in the group. At the time of bidding, this value is unknown to all participants. 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 horizontals 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**

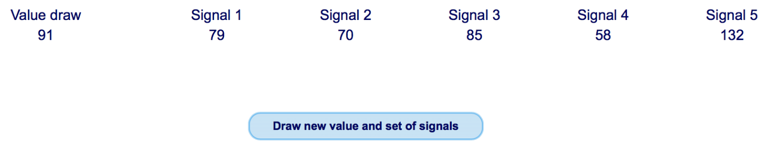
First, a value of the product is randomly determined, but not revealed to the participants. In our example, this value will be 121. Then, based on the value of 121, the signal for each participant will be drawn. The following signals are drawn: one bidder receives a signal of 60, one bidder a signal 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. *f*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. *f*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.*g* 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.*g* *f*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.*g*

**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 13: 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.

## B.2 Additional elicitations

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

### B.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.

*Payo*

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.

#### B.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.

*Payo*

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.

## B.3 Screenshots of the interface

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

Figure 14: Screenshot from a ascending Vickrey auction.

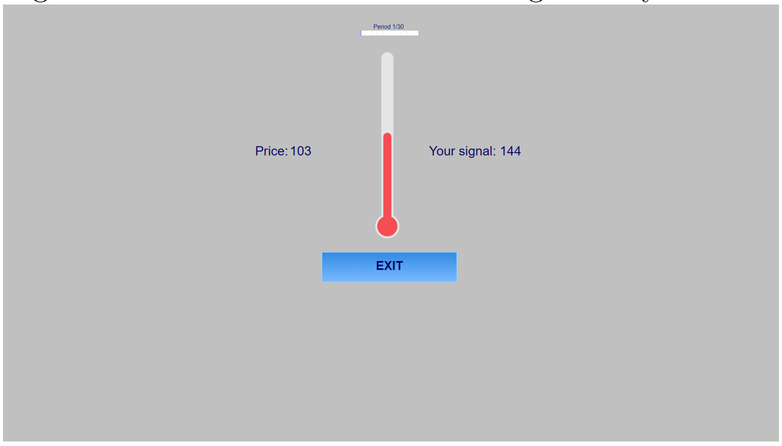



Figure 15: Screenshot from a Japanese English auction.

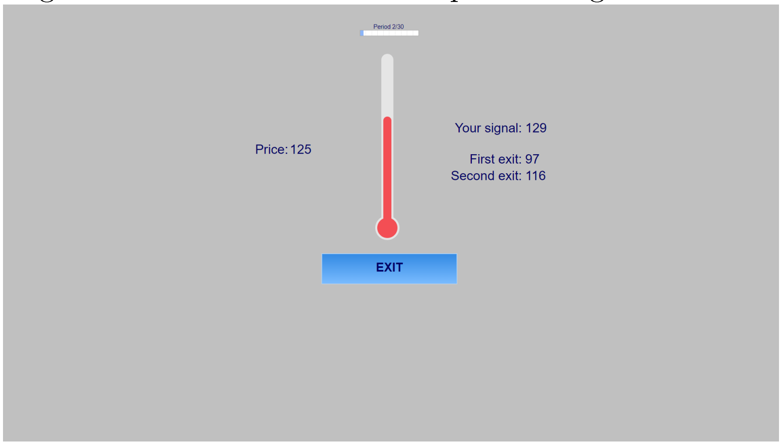



Figure 16: Screenshot from an oral outcry auction.