The Missing "Loser's Curse": Experimental Evidence on Belief-Based Models in Common-Value Auctions*

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Abstract

Belief-based models such as Cursed Equilibrium and Level-k Thinking are some of the leading explanations for the Winner's Curse observed in common-value auctions. We argue that these models predict a Loser's Curse in other auctions formats. Using an experiment with a within-subject design, we test for the presence of the Winner's Curse and the Loser's Curse in uniform-price auctions with common values. At the aggregate level, we find evidence of a strong Winner's Curse, but no evidence of a Loser's Curse. These aggregate findings cast some doubts on the ability of belief-based models to fully explain the Winner's Curse. Indeed, at the individual level, the behavior of most subjects is better described by Joy of Winning and Quantal Response Equilibrium. We also find suggestive evidence of failures of contingent thinking: subjects behave somewhat closer to the rational benchmark in a non-strategic environment when the relevant contingency is made more salient.

JEL Classification: C91; C92; D44; D91.
Keywords: Auctions; Winner's Curse; Overbidding; Failure of Contingent Thinking.

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1 Introduction

Common-value auctions are those where all bidders value an asset similarly, but have partial and differing information (i.e., a signal) about its actual worth. A classic example is an auction for natural resources like oil or timber, but common-value elements can also appear in auctions for assets such as houses or paintings. In these cases, bidders' valuations are shaped by their private preferences and the potential resale value, which introduces an aspect of shared valuation.

A large experimental literature on common-value auctions has found that subjects tend to systematically overbid. In particular, several studies have found evidence of the Winner's Curse: the winner bids so high that she ends up paying a price that exceeds the value of the item.[1] The existence and ubiquity of the Winner's Curse is one of the most robust findings in the experimental literature on auctions.[2] Moreover, the Winner's Curse can also manifest itself in bilateral-trade experiments, as shown by Samuelson and Bazerman (1985), Holt and Sherman (1994), and Charness and Levin (2009). This evidence, however, is at odds with the standard prediction of Bayes Nash equilibrium where, in a symmetric environment, buyers realize that winning the auction entails holding the most optimistic signal, and thus correctly account for the implied adverse selection.

Two popular explanations for the Winner's Curse are "Cursed Equilibrium" (Eyster and Rabin, 2005) and "Level-k Thinking" (Crawford and Iriberri, 2007). The first is an equilibrium model where a player underestimates the degree to which his opponents' actions are correlated with their private information; the latter is a non-equilibrium model of iterated best responses. These two models share the feature that bidders fail to correctly condition on the negative information conveyed by winning the auction, leading to systematic overbidding. However, this same reasoning leads to *underbidding* in other auction formats. Indeed, as pointed out by Pesendorfer and Swinkels (1997), in auctions with multiple (identical) units, bidders may be also exposed to a "Loser's Curse": losing the auction conveys the positive information that several other bidders had higher signals. In these auctions, therefore, a bidder who fails to properly condition on the information conveyed by losing the auction may end up bidding too low, thereby missing out on a profitable transaction.[3]

In this paper, we present the results from an experiment with a within-subject design aimed at testing for the presence of both curses in common-value auctions. We do so by studying subjects' bidding behavior in *uniform-price* auctions with five bidders, where there can be several homoge-

[1] The first use of the term is by Capen et al. (1971) in the context of the early Outer Continental Shelf (OCS) oil lease auctions ("In fact [...] the Gulf has paid off at something less than the local credit union."). The term is often used to describe bidders suffering monetary losses, but a less extreme view is that the Winner's Curse results in lower than "normal" (or equilibrium) profits. See also Kagel and Levin (2002).

[2] See, for example, Bazerman and Samuelson (1983), Kagel and Levin (1986), Lind and Plott (1991), Levin et al. (1996), Avery and Kagel (1997), Ivanov et al. (2010), Levin et al. (2016), Koch and Penczynski (2018), and Charness et al. (2019). While we will discuss in detail the contributions most closely related to our paper, this literature is too voluminous for us to summarize here; hence, we refer the reader to the excellent survey by Kagel and Levin (2016).

[3] Holt and Sherman (1994) find evidence of the Loser's Curse in the context of bilateral negotiations.

neous items for sale and all items are sold for the same price. By varying the number of items for sale, we can manipulate whether a bidder is exposed to either the Winner's Curse or the Loser's Curse, holding fixed the information she has about the item's value and the number of competitors she faces. In particular, when there is only one prize for sale, buyers face a standard second-price auction in which the highest bidder wins and pays the second-highest bid; as it is well known, the winner in this auction could fall prey to the Winner's Curse. With four prizes instead, the four highest bidders all get one item each and pay a price equal to the lowest bid; thus, the losing bidder in this auction could suffer from the Loser's Curse.

At an aggregate level, we observe a significant Winner's Curse in the one-prize auction, consistent with prior findings in the literature. While a sizable proportion of subjects tend to underbid in the four-prize auction, especially when they have a high signal, we do not find evidence for the Loser's Curse. This suggests that belief-based models like Cursed Equilibrium and Level-k Thinking might not be capturing all of the drivers for the Winner's Curse.

A more recent literature suggests that individuals may suffer from a failure of contingent thinking; in a common-value auction, this entails that a bidder would fail to condition her bid on the hypothetical event that they win. This failure is not due to bidders having incorrect beliefs about the behavior of their competitors; rather, it may be due to individuals either being unable to, by themselves, conceive of the event of being pivotal or, even if they are able to construct it, fail to pay attention to it. Nevertheless, failures of contingent thinking, like Cursed Equilibrium or Level-k, would also predict that subjects should experience the Loser's Curse in our four-prize auction. For experimental evidence of failure of contingent thinking, see Charness and Levin (2009), Esponda and Vespa (2014), Martínez-Marquina et al. (2019), Ngangoué and Weizsäcker (2021), Aina et al. (2024), and Esponda and Vespa (2024); for an overview of the literature, see Niederle and Vespa (2023). Overall, these contributions show that experimental subjects tend to fare better when they are explicitly told about or put in the relevant contingency.

In order to evaluate the importance of failures of contingent thinking for common-value auctions, subjects in our study also took part in a non-strategic valuation task. Keeping the common value of the prize and subjects' signal about it fixed, we informed them of how their signal ranked against others' and then elicited their willingness to pay for the prize. Notice that conditioning on the information about one's signal rank is an operation akin to the one that a bidder should perform in the symmetric Bayes Nash equilibrium of the auctions; yet, a subject's beliefs about how others bid are immaterial for this task. Our results indicate that subjects overbid for all signals, but their bids in this task are closer to the rational benchmark than in the auctions. Hence, it appears that providing subjects with the relevant information to condition on helps them to some degree.

Going beyond the analysis of aggregate-level behavior, we find substantial heterogeneity at the individual level. Moreover, these differences in behavior between subjects are consistent: both the overall levels and the responsiveness of bids to signals show strong positive correlations across the two types of auction. Thus, there is a potential for behavioral models to explain behavior, and the best model might differ by subject. We take a structural approach and estimate the parameters of several behavioral models for every subject, then classifying each subject as choosing according to the model with the lowest associated Akaike information criterion (AIC; Akaike, 1974). In addition to Cursed Equilibrium and Level-k Thinking, we consider two models that have been shown to explain deviations from equilibrium bidding in private-value auctions: Quantal Response Equilibrium (QRE) and the "Joy of Winning" hypothesis.[4] The majority of our subjects are classified as bidding as if they have a Joy of Winning, while a smaller proportion chooses according to QRE. Only a handful of subjects are classified as behaving according to Level-k Thinking or Cursed Equilibrium.

Overall, our findings suggest that models of limited strategic thinking (such as Cursed Equilibrium and Level-k) and failures of contingent thinking, while identifying some of the reasons why bidders deviate from Nash equilibrium in common-value auctions, do not capture the full psychology of how subjects tend to bid in these auctions. Indeed, in our data we observe a generalized tendency to overbid, consistent with the Joy of Winning hypothesis, as well as significant noise, perhaps due to subjects' inability to correctly form conditional expectations or other forms of optimization mistakes, as suggested for instance by QRE.

The paper proceeds as follows. Section 2 describes our experimental design and the theoretical framework that motivates it. Section 3 presents our results at an aggregate level, discussing the extent to which they are consistent with the winner's and loser's curses; this section also shows that behavior in the non-strategic task is closer to the rational benchmark. Section 4 presents the individual-level analysis, comparing several behavioral models according to how well they describe each individual's bidding behavior in uniform-price auctions. Section 5 provides a discussion of our findings and offers concluding remarks. The remainder of this section discusses the literature most closely related to our paper.

Related Literature

We contribute to the extensive experimental literature on common-value auctions and the Winner's Curse. Most of this literature has focused on first-price and second-price sealed-bid auctions, starting from the "Jar Experiment" of Bazerman and Samuelson (1983) who, using a first-price auction, auctioned the contents of four different jars full of coins to MBA students, with the common value being the sum of the coins in the jar; they found that although subjects tended to underestimate the value of the jar, the average winning bid was 25% higher than the true value. Since then, the canon-

[4]Goeree et al. (2002) show that QRE can explain the overbidding observed in first-price auctions. Cox et al. (1988) and Cooper and Fang (2008) show that Joy of Winning can rationalize overbidding in first-price and second-price auctions, respectively.

ical framework employed in this literature, which was first developed by Kagel and Levin (1986), has the common value being drawn from a uniform distribution. Subjects know the distribution from which the value is drawn, but they do not observe its realization; instead, they observe an unbiased iid signal of the value, which is also conditionally uniformly distributed.[5] Using the same framework, Levin et al. (1996) analyze English auctions, while Levin et al. (2016) focus on Dutch auctions. All of these studies document that bidders, including experienced ones, fall prey to the Winner's Curse.

Our study slightly departs from the literature mentioned above in two ways. First, for the common value we use the "Wallet Game" (Klemperer, 1998) formulation, where the value of the prize is given by the sum of all bidders' signals; for other experimental studies that employ this formulation, see Avery and Kagel (1997), Goeree and Offerman (2002), and Moser (2019).[6] Second, we consider uniform-price auctions of multiple, identical items. The experimental literature on uniform-price auctions has mostly focused on the case where bidders have private values and demand more than one unit; in this case, bidders have an incentive to reduce demand in an effort to obtain more favorable prices on the items they win (List and Lucking-Reiley, 2000; Kagel and Levin, 2001). By contrast, we focus on a common-value environment where bidders demand only one unit; we chose this setting in order to generate the opportunity for bidders to suffer from the Loser's Curse, while keeping the environment as similar as possible to that of a second-price auction.

The literature on the Loser's Curse is much less developed than the one studying the Winner's Curse. Yet, both curses stem from the same underlying mistake, namely a form of selection neglect.[7] This point was first made by Holt and Sherman (1994) in the context of bilateral trading. In particular, they experimentally examined three versions of the "Acquiring-a-Company Game" of Samuelson and Bazerman (1985); in one of the versions, the distribution of the seller's types is such that if a buyer fails to properly condition on her offer being accepted, she will tend to bid too low, thereby failing to make a profitable acquisition.[8] Indeed, they find evidence of the Loser's Curse, with subjects bidding 20% below the rational benchmark. As pointed out by Pesendorfer and Swinkels (1997), in uniform-price common-value auctions, bidders are simultaneously exposed to both curses; and a rational bidder should be able to avoid both. To the best of our knowledge, we are the first to design an experiment aimed at testing for the presence of the Loser's Curse in common-value auctions.

[5]For studies that employ this framework see Dyer et al. (1989), Lind and Plott (1991), Kagel and Richard (2001), Casari et al. (2007), Koch and Penczynski (2018), and Nagel et al. (2024).

[6]Yet another formulation also employed in the literature is the "Maximum Game" (Bulow and Klemperer, 2002), where the common value coincides with the maximum of the signals; for experimental studies that use this formulation, see Ivanov et al. (2010) and Camerer et al. (2016).

[7]Massey and Thaler (2013) use the term when describing how top NFL draft picks are significantly overvalued in a manner that is inconsistent with rational expectations and efficient markets; yet, the mechanism we highlight is different.

[8]Holt and Sherman (1994) describe such bidder as being naïve; this is equivalent to a fully cursed bidder in the language of Eyster and Rabin (2005).

Finally, we also contribute to a more recent experimental literature on failures of contingent thinking. Roughly speaking, a failure of contingent thinking arises when agents are able to select the optimal action when a problem is presented in a way that helps them focus on all relevant contingencies, but fail to optimize if the problem is presented without such aids.[9] Failures of contingent thinking have been observed in voting games (Esponda and Vespa, 2014), Ellsberg-type and Allais-type decision problems (Esponda and Vespa, 2024), public-good games (Calford and Cason, 2024), and in "Acquiring-a-Company" problems (Charness and Levin, 2009; Martínez-Marquina et al., 2019). More relevant for our study, Koch and Penczynski (2018), Moser (2019), and Nagel et al. (2024) find evidence of failures of contingent thinking in the context of common-value auctions; however, there are several differences between their designs and ours. Koch and Penczynski (2018) compare bidding between a first-price auction and a transformed version of this auction that does not require conditional reasoning, and find that overbidding decreases significantly in the latter. Moser (2019) considers two-bidder second-price auctions in which bidders are offered the opportunity to change their bid after learning whether it was the winning one; he finds that indeed subjects revise their bids, although not always for the better. Finally, Nagel et al. (2024) have a multi-part experimental design aimed at identifying the key driving factors of the Winner's Curse using a first-price auction. In one part, they inform subjects that they will only participate in auctions in which they have the highest signal. Such announcement would be immaterial if subjects were already conditioning their bids on having the highest signal; yet, they find that subjects significantly revise their bids downward. In contrast to these studies, in our experiment we test for failures of contingent thinking using a non-strategic task; we find that subjects' decision-making improves when they are provided with the relevant information to condition on, but it is still far from the rational benchmark.

2 Experimental Design

In this section, we describe the details of our experiment. Section 2.1 outlines the theoretical framework that underpins our experimental design, together with the predictions of the symmetric Bayes Nash equilibrium benchmark. Section 2.2 describes our experimental implementation.

2.1 Theoretical Framework

There are $N \geq 2$ bidders, labeled $i = 1, \ldots, N$, and K identical items, with $N > K \geq 1$. Each bidder i privately observes a signal $s_i \in [\underline{s}, \overline{s}]$; signals are independently drawn from the same distribution $F(\cdot)$ which admits a smooth strictly positive density $f(\cdot)$. We often refer to a bidder's signal as her type. Each bidder wants at most one item. The value of an item is the same for (but

[9] A related notion is that of an obviously strategy-proof mechanism introduced by Li (2017).

unknown to) all bidders, and is given by

$$V(s_1, \ldots, s_N) = \sum_{i=1}^{N} s_i. \tag{1}$$

In our experiment, we are going to focus on so-called uniform-price auctions. In such auctions, bidders simultaneously submit sealed bids and the winning bidders are all charged the amount of the highest rejected bid. Hence, if there are K items, the K highest bidders each receive an item and pay a price p given by the $K+1$st highest bid; this procedure generalizes the single-object second-price auction. A bidder's payoff is equal to $V - p$ if she obtains an item and to zero otherwise.[10]

Let $s_{(1)} \geq s_{(2)} \geq \ldots \geq s_{(N)}$ denote the order statistics of the bidders' types. Of central importance to any given bidder is the distribution of the types of the other bidders. Hence, taking the point of view of bidder i, let $y_1 \geq y_2 \geq \ldots y_{N-1}$ denote the order statistics of the types of bidder i's competitors. Then, as shown by Pesendorfer and Swinkels (1997), the unique symmetric Bayes Nash equilibrium strategy in a uniform-price auction for K items is given by

$$\beta_K(s_i) = \mathrm{E}[V | y_K = s_i, s_i]. \tag{2}$$

In words, bidder i submits a bid equal to the expected value of an item conditional on (i) her signal, and (ii) tying with her opponent with the Kth highest signal.

Finally, we introduce two additional functions that will play an important role in our experimental design. First, we let $\mathrm{E}[V|s_i]$ denote bidder i's expectation of the value of the item conditional on her own signal. Next, we define bidder i's expected value conditional on her signal and on knowing how her signal ranks compared to those of the other bidders as

$$\beta_{RV}(s_i, r) = \mathrm{E}[V | s_i, r] \tag{3}$$

where $r \in \{1, 2, \ldots, N\}$ denotes the rank of bidder i's signal; e.g., $r = 1$ means that bidder i has the highest signal.

2.2 Experiment

We carried out a laboratory experiment exploring the setting described in Section 2.1. In particular, subjects participated in two auction tasks: an auction with $K = 1$ ("one-prize auction") and another with $K = 4$ ("four-prize auction"). Each auction had $N = 5$ and the common value of the prize was as in (1), with private signals distributed uniformly on $[0, 5]$ and drawn independently across subjects.

[10]Thus, we assume that bidders are risk neutral; yet, the analysis would be qualitatively similar under other risk attitudes so long as these are homogeneous across bidders.

In this setting, expression (2) becomes

$$ {}_1(s_i) = 3.5 s_i \tag{4}$$

for $K = 1$, and

$$ {}_4(s_i) = 7.5 + 3.5 s_i \tag{5}$$

for $K = 4$. Therefore, in our experimental implementation, the equilibrium bid in the four-prize auction has the same slope as that of the one-prize auction, but it is shifted upward by 7.5. Moreover, there is an underlying equivalence between these two auctions: The difference in payoffs for player i, $i = 1, ..., 5$, from bidding b_i or b_i' in the one-prize auction, given signals $s_1, \ldots, s_5$ and the bids b_j, $j \neq i$, of the other players, is the same as the difference in payoffs from bidding $25 \quad b_i$ or $25 \quad b_i'$ in the four-prize auction, given the transformed signals $5 \quad s_1, \ldots, 5 \quad s_5$ and transformed opponent bids $25 \quad b_j$. Given that the distribution of s_i is symmetric, this implies that an equilibrium in one auction can be used to recover an equilibrium in the other.[11]

Subjects in our study also completed a non-strategic valuation task in which, after being informed of their signal's ranking, they had to indicate their maximum willingness to pay to acquire the same common-value prize. In theory, this willingness to pay should coincide with expression (3), which in this setting is given by

$$ {}_{RV}(s_i; r) = 3 s_i + 2.5(r \quad 1) \tag{6}$$

for $r = 1, 2, ..., 5$. Importantly, notice that

$$ {}_{RV}(s_i; 2) \qquad {}_1(s_i) > \quad {}_{RV}(s_i; 1)$$

and

$$ {}_{RV}(s_i; 5) \qquad {}_4(s_i) > \quad {}_{RV}(s_i; 4).$$

These inequalities provide us with meaningful bounds that allow us to check whether, when bidding in the auctions, subjects condition on the relevant contingency (provided that they choose correctly in the valuation task).

Overall, 120 subjects participated in our study, split across five experimental sessions that took place at the experimental laboratory of the Centre for Unified Behavioural and Economic Sciences (CUBES) of the University of Queensland in March 2024. Summary statistics of subject demographics can be found in Table 4 of Appendix A.1.

Each session began with the experimenter reading the instructions aloud; subjects were also

[11] We thank Joel Sobel for suggesting the existence of this transformation.

presented with the same instructions both on paper and on their screen.[12] After all instructions had been read, subjects were presented with a detailed example showing a group of five participants, their signals, their choices in each task, and the associated outcomes. The subjects then completed a quiz to test their understanding of each task. After all subjects completed the quiz, they went on to complete 20 rounds of the experiment. At the end of the experiment, one decision within one round was chosen at random to be paid. Sessions lasted between 100 and 120 minutes. Subjects received an average payment of $52.55.[13]

The experiment used a within-subject design with three treatments. In the first treatment, subjects participated in a one-prize second-price auction. In the second treatment, subjects participated in a four-prize fifth-price auction. In the third treatment, subjects participated in a nonstrategic purchasing task. On the bottom of each decision page, subjects were presented with a short reminder of the instructions that were relevant for their decisions.

In the **bidding stage**, subjects were reminded of the structure of the common value and of the distribution of the signals. Then they were informed of the realization of their own signal. Subjects made bids in both the one-prize auction and the four-prize auction on the same page. Bids were made using sliders that were not initialized and had to be clicked to be activated. Bids could be made in $0.20 increments. After activating the sliders, subjects clicked next to move to the next stage. An example of a bidding stage interface can be found in Figure 1.

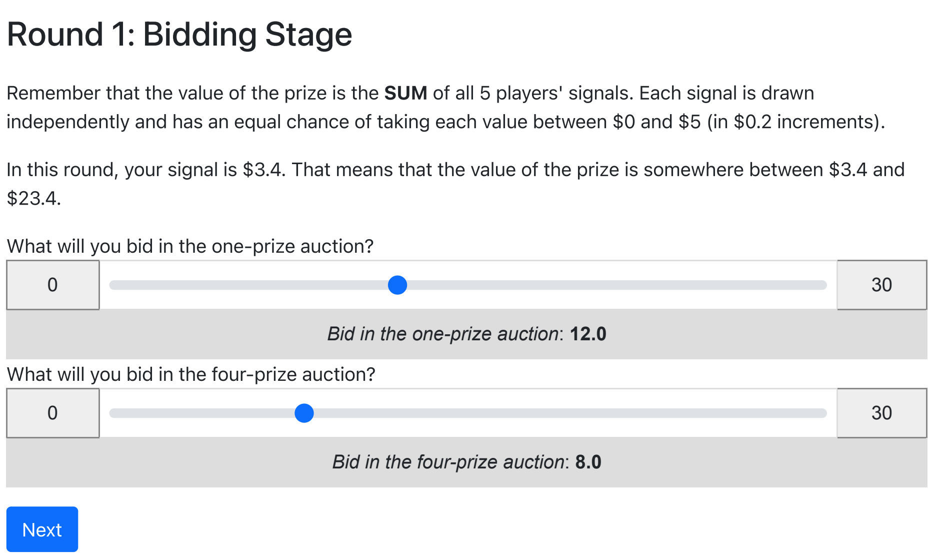

Figure 1: Bidding Stage

In the **purchase stage**, subjects were again reminded of the structure of the common value and of the distribution of the signals, as well as the realization of their own signal. They were then told

[12] Screenshots of instructions and all parts of the experiment can be found in Online Appendix C.

[13] Throughout the paper, the symbol $ denotes Australian dollars.

the *rank* of their signal, as it compared to the other members of their group.[14] Subjects were then asked to provide the maximum price they would be willing to pay to receive the prize. This price was reported using a slider, which was not initialized and had to be clicked to be activated. The slider moved in \$0.20 increments. This task was incentivized using a Becker-Degroot-Marschack mechanism (BDM; Becker et al., 1964), in which a random price was drawn on the interval from \$0.20 to \$30. If the price was below the reported maximum price, then the subject won the prize and paid the random price.[15] An example of a purchase stage interface can be found in Figure 2.

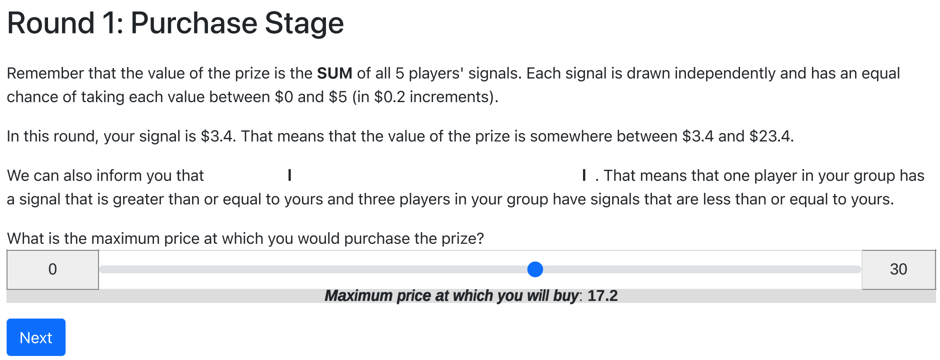

Figure 2: Purchase Stage

In both the bidding stage and the purchase stage, subjects were given a "budget" of \$30 out of which they made their bids or their purchasing choices. This was implemented to avoid losses.

After completing both the bidding stage and the purchase stage, subjects were informed of the outcome of each task within the round. Specifically, they were informed of the overall value of the prize, the second-highest bid in the one-prize auction, the lowest bid in the four-prize auction, and the randomly drawn price.[16] They were informed of their payoffs from each decision task, and reminded that if this round was selected for payment, each task was equally likely to be chosen to be the one that counted. An example of the feedback given can be found in Figure 3.

[14] A fully rational decision maker should be able to update the possible range of the common value based on the additional information provided by the rank. We did not do this computation for the subjects exactly because we are interested in testing their ability to correctly update.

[15] As a decision aid, the interface of the purchase stage also included an interactive feature helping subjects to understand at what prices they would purchase. Each purchase stage has a table containing values between \$0.20 and \$30 in \$0.20 increments. After activating the slider, the table was filled in with either an ✗ or a ✓next to each price, indicating to subjects at what prices they would purchase. An example can be seen in Figure 30 of Appendix C.

[16] There are a variety of approaches regarding feedback in experimental common-value auctions. At one end of the spectrum, Garvin and Kagel (1994) and Casari et al. (2007) show all bids and their associated signals at the end of each round. On the other hand, Ivanov et al. (2010), Camerer et al. (2016) and Moser (2019) provide no feedback at all. Our approach is more balanced and resembles that of Ngangoué and Schotter (2023).

Figure 3: Feedback

After subjects completed all 20 rounds, they were informed of their payments from the experiment and completed a short survey. They reported basic demographic information, completed a Cognitive Re ection Test (CRT; Frederick, 2005), and gave feedback about the experiment.

3 Aggregate Results

We start our analysis by describing our results at the aggregate level. Section 3.1 discusses the extent to which both the Winner's and Loser's curses are present in our auction data. Section 3.2 compares the bidding patterns in our experiment with the predictions of the symmetric Bayes Nash equilibrium; moreover, we also show that experience helped subjects in our experiment slightly improve their bids, but only in the one-prize auction. Finally, Section 3.3 presents the results of the non-strategic task, showing that subjects' choices seem to improve when they are directly provided with the relevant information on which to condition their bids.

3.1 Payoffs: Winner's and Loser's Curse

We begin by asking two simple but crucial questions about the payoffs in these auctions. First, do winners of one-prize auctions fall prey to the Winner's Curse? And, second, do losers of the four-prize auctions suffer from the Loser's Curse?

Many previous papers have found evidence of the Winner's Curse in common-value auctions (Kagel and Levin, 1986; Avery and Kagel, 1997; Goeree and Offerman, 2002; Ivanov et al., 2010; Camerer et al., 2016; Levin et al., 2016). We say that a winner is subject to the Winner's Curse if their empirical payoffs are lower than what they would have received had they bid lower and lost the auction.[17] Rational bidders should not, on average, lose money from winning.

[17]We could also de ne a “Weak Winner's Curse” as winners receiving lower payoffs than what are predicted by

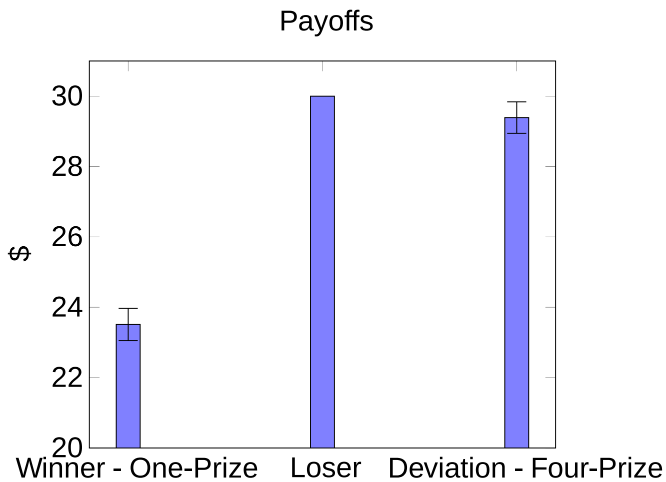

Figure 4: Cursed Payoffs. "Winner - One-Prize" shows the average payoffs of winners in the one-prize auction, and "Deviation - Four-Prize" shows the payoffs that losers of the four-prize auction would have received had they bid high enough to win. Winners of the one-prize auction would earn higher payoffs on average if they had bid zero and lost, but losers of the four prize auction would not earn higher payoffs if they had maximized their bid and guaranteed themselves a win.

Result 1. Winners of the one-prize auctions are subject to the Winner's Curse on average.

Figure 4 shows the average payoffs that winners of the one-prize auctions received as compared to the payoffs that they would have received had they lost the auction. Winners of the one-prize auctions receive less than $24 on average, and this average is statistically different from $30 ($p < 0.01$). In contrast, winners in the four-prize auction are not subject to the Winner's Curse, as they receive $33.78 on average.

As discussed in the Introduction, the classical argument that leads to the Winner's Curse in the one-prize auction also suggests the existence of a Loser's Curse in the four-prize auction. In particular, the Loser's Curse would imply that buyers who lose the auction would have been better off if they had deviated to a higher bid, winning the auction at a price equal to the next lowest bid. We say that such a loser is subject to the Loser's Curse. This gives a natural empirical measure of the Loser's Curse: In each four-prize auction, we compute the payoff a buyer would receive if they won the auction at a price equal to the fourth-highest bid, and refer to this as the "Deviation".

Result 2. Losers of the four-prize auction are not subject to the Loser's Curse.

The evidence for Result 2 can again be found in Figure 4. The payoff associated with the deviation is not above the payoff that buyers receive from losing in these auctions, indicating that there is no evidence of a Loser's Curse.[18]

Nash Equilibrium. Because our data shows evidence of the Winner's Curse holding on average, it necessarily also shows evidence for this Weak Winner's Curse to hold on average.

[18] As with the "Weak Winner's Curse" (see Footnote 17) we could define the "Weak Loser's Curse" as the empirical

3.2 Bidding and Experience

Figure 5 shows average bids along with their 95% con dence intervals for each signal and both types of auction. While the con dence intervals for the average bids overlap for all signals, Table 5 in Appendix A.1 shows that the average difference between bids in the two types of auction is \$1.58, and this difference is statistically signi cant at the 1% level.

Figure 5: Averages vs. Theories in Auctions

Result 3. In one-prize auctions, buyers overbid on average for almost all signals. In four-prize auctions, buyers overbid for low signals but underbid for high signals.

Result 4. Average bidding functions in both types of auction have intercepts that are higher and slopes that are lower than their respective rational benchmarks.

Evidence for results 3 and 4 can be seen in Figure 5, but we provide formal statistical analysis in Table 1.[19] Columns (1) and (2) estimate linear bidding functions in the one-prize and four-prize auctions, respectively. As discussed in Section 2.2, according to the symmetric Bayes Nash

deviation payoffs being higher than the deviation payoffs implied by the Nash Equilibrium, which can be calculated at 29.166. While the empirical deviation payoffs are higher than this at 29.392, the difference is not signi cant ($p = 0.32$).

[19] This table takes the exact form that we preregistered in our preanalysis plan.

equilibrium the slopes of both functions should be equal to 3.5, and the intercepts should be 0 and 7.5, respectively.

Table 1: Choices

	(1) One-Prize-Bid	(2) Four-Prize-Bid	(3) Reservation Price
Signal	0.77	0.65	1.22
	(0.091)	(0.077)	(0.17)
Highest Signal			-2.74
			(0.76)
Second Highest Signal			-1.78
			(0.69)
Third Highest Signal			-0.81
			(0.60)
Fourth Highest Signal			-0.67
			(0.54)
Constant	13.4	15.3	12.7
	(0.22)	(0.19)	(0.34)
Observations	2400	2400	2400

Notes: Linear regression with subject- and round- xed effects and standard errors clustered at the subject level. Signi cance indicated by: *** p< 0.01, ** p< 0.05, * p< 0.1.

Figure 6 shows how average bidding functions change after subjects have experience, which we de ne as having completed ten rounds. The second column in Table 5 of Appendix A.1 shows that there is no statistically detectable difference between average bidding in the one-prize and four-prize auctions when subjects are inexperienced, but this gap increases to $2.39 and becomes signi cantly different from zero once subjects have gained experience. Despite this, even with experience, it remains well below 7.5, the level predicted by Bayes Nash equilibrium.

In Table 7 in Appendix A.1, we show how our results differ for subjects that have higher ability, as measured by above-median CRT scores or quiz scores. Because Table 1 already includes subject xed effects, the intercept does not change. Instead, the table shows how responsiveness to the signal varies with ability level. The only relationship that is signi cant is the positive interaction between above-median CRT scores and the signal in one-prize auctions: subjects with higher CRT scores are roughly twice as responsive to their signal as subjects with lower CRT scores.

3.3 Failures of Contingent Thinking

We now turn to whether decision-making improves when subjects are directly provided with the information that should be relevant for their decision. Figure 7 reports average willingness to pay

(a) One-Prize (b) Four-Prize

Figure 6: Effects of Experience. There is slight learning in one-prize auctions, with bids decreasing signi cantly by rounds 11-20. Average bids in the four-prize auction do not change signi cantly with experience.

conditional on signal, normalized across ranks by the theoretically predicted effect of the rank information (subtracting 10 conditional on the lowest rank, 7.5 conditional on the fourth-highest rank, etc.). This gure provides evidence for Result 5.

Figure 7: Average Value vs. Theory – Pooled and Rescaled

Result 5. Average willingness to pay is slightly higher than the theoretically predicted rational benchmark for all signals.

We summarize how the differences between choices and the rational benchmark vary across treatments in Table 2. In Column (1), the dependent variable is the difference between a subject's choice and the theoretical prediction, while the independent variables are indicators for the decision task being faced (with the valuation task being the omitted category). The results con rm substantial overvaluation in the valuation task and overbidding in the one-prize auction ($p < 0.01$ for both tests). Overbidding in the four-prize auction is also statistically different from zero ($p = 0.04$), but the difference is substantially smaller. The dependent variable in column (2) is the absolute value of the difference between choice and theory. This provides the evidence for Result 6: The significant positive coefficients for both auctions indicate that average absolute differences between choices and the rational benchmark are smaller in the valuation task than in either type of auction.

Result 6. Decision-makers choose closer to the rational benchmark when provided with the relevant contingent information.

The fact that subjects' behavior is closer to the rational benchmark in the valuation task than in the auctions is consistent with the recent findings on failures of contingent thinking. Moreover, the fact that subjects still overbid even in a non-strategic task, where beliefs about others are irrelevant, suggests perhaps a more general tendency to bid high, which we will explore in the next section.

Table 2: Deviations from the Rational Benchmark

	(1) Difference from Theory	(2) Abs. Difference from Theory
One-Prize	4.51	2.62
	(0.49)	(0.29)
Four-Prize	-1.41	1.13
	(0.57)	(0.28)
Constant	2.13	5.91
	(0.30)	(0.14)
Observations	7200	7200

Notes: Linear regression with subject-round fixed effects and standard errors clustered at the subject level. Significance indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Table 6 of Appendix A.1, we report the second part of our pre-registered analysis. Here, we analyze how decisions vary across the three tasks conditional on rank, and using subject-round fixed effects. Following the discussion in Section 2.2, we should observe that bids in the one-prize auction are higher than valuations for signal rank one, but lower than valuations for signal ranks two to five. Similarly, bids in the four-prize auction should be higher than valuations for signal ranks one to four, but lower than valuations for signal rank five. Instead, we find that bids are higher than valuations for both auctions and all signal ranks, although this relationship is not significant for ranks three to five in the one-prize auction. Furthermore, we show how the relationship between valuation and signal varies by subject ability in Table 8 of Appendix A.1. Subjects that have above-median CRT or quiz scores tend to be more responsive to both their signal and the rank of their signal.

(a) Estimated Slopes (b) Estimated Intercepts

Figure 8: Estimated Linear Bidding Functions. The line provides the best- tting linear relationship between the estimated parameters.

4 Comparison of Different Behavioral Models: Individual-Level Results

In this section, we focus on behavior at the individual level, with the goal of identifying which behavioral model best describes each subject. Before considering the models, we summarize individual behavior in the auctions in Figures 8 and 9.

Figure 8 reports the coef cients resulting from estimates of linear bidding functions for each subject and relates them across auctions. Panel (a) shows the estimated slopes and panel (b) reports the estimated intercepts. Two conclusions can be drawn from these gures. First, most estimates are far from the rational (Nash Equilibrium) benchmark. Second, there is substantial heterogeneity and consistency at the individual level. Parameters for individuals vary widely, and there is a strong positive relationship between estimated parameters in the two auctions. We take these points as evidence that behavioral models can be useful to explain behavior in these common-value auctions, and that there may be substantial heterogeneity in which model best captures an individual's behavior.

Additional evidence of the importance of heterogeneity can be found in Figure 9. For each subject, the gure reports the number of rounds in which their bid in the one-prize auction was strictly greater than, equal to, or strictly less than their bid in the four-prize auction. Eleven subjects always bid strictly higher in the four-prize auction than in the one-prize auction, while ve subjects always bid strictly higher in the one-prize auction; recall that according to the rational benchmark, bids in the four-prize auction should always be higher than those in the one-prize auction. Moreover, as the gure shows, just a few subjects are responsible for the majority of rounds in which bids in the two auctions were exactly the same.

Figure 9: Bid Orders - Individuals

4.1 Individual-Level Classification

In the following sections, we report individual estimates for the four behavioral models we consider: Quantal Response Equilibrium, Cursed Equilibrium, Level-k Thinking, and Joy of Winning. To estimate the models, we assume that buyers choose according to a logit stochastic choice function given the model's parameters and the payoffs implied by those parameters. This allows us to estimate each model's parameters using maximum likelihood, while allowing for noisy decision-making.

Estimating the parameters of each model for each individual allows us to classify individuals according to the model that predicts their behavior the best. The models that we use differ in terms of the numbers of parameters that must be estimated for each of them, so we compare these models using the Akaike information criterion (AIC). The full set of AICs for each subject and model we consider can be found in Appendix B.

Figure 10: Proportions of Estimated Types

Figure 10 reports the proportions classified as each type. We can see that 80 subjects are classified as being best described by having a Joy of Winning. This is followed by Quantal Response Equilibrium and Level-k Thinking, with 32 and 7 subjects classified, respectively. Finally, 1 subject is classified as choosing according to Cursed Equilibrium.

4.2 Quantal Response Equilibrium

Quantal Response Equilibrium (QRE) is a solution concept in which players act as if they have correct beliefs about the information and actions of others, but do not necessarily best respond to these beliefs (McKelvey and Palfrey, 1995). Instead, the likelihood that a choice is made is positively related to the payoffs that the choice leads to. Following much of the previous literature, we focus on the logit implementation of QRE, in which choice probabilities can be calculated based on a logit distribution (Goeree et al., 2016).

QRE has been successfully used to explain behavior in experimental auctions (Goeree et al., 2002; Camerer et al., 2016). In many types of common-value auctions, because players do not always choose in a deterministic and increasing way in relation to their signals, the inference that can be drawn from a set of bids is weaker and best-response functions are less steep than under Nash Equilibrium. We show computed QRE average bidding functions for various levels of the logit noise parameter in Appendix A.2.

In our empirical approach, we allow for subjects to have a different logit noise parameter; thus, our results are closer to the *heterogeneous* quantal response equilibrium discussed in Rogers et al. (2009). The relevant parameters that we estimate for QRE are the λ's from the logit stochastic choice function. We estimate these following the general approach discussed in Camerer et al. (2016). First, we compute a buyer's expected payoff in the experiment conditional on any combination of signal and bid for each auction.[20] Given these payoffs and the choices made by the subject, we estimate the logit parameters, restricting them to be greater than zero (so choices are required to be positively correlated with payoffs).

Panel (a) of Figure 11 shows the results of this estimation procedure. The estimated parameters have a correlation coefficient of 0.47 (statistically significantly different from zero with a *p*-value of less than 0.01). The estimates for subjects that are classified as QRE bidders are shown in blue circles, while those classified as choosing according to one of the other models have red x's. Those that are classified as QRE tend to have higher values of λ_1, the parameter that captures how noisy decision-making is in one-prize auctions. Panel (b) of the same figure shows the actual choices of a subject classified as QRE, along with the model's predicted modal choice.

[20] We compute this based on the joint empirical distribution of signals and bids. We draw four observations of bid-signal pairs at random from the full experiment. Given this artificial set of other bids, we compute the payoff a buyer would receive for every combination of bid and signal. We repeat this exercise a total of 100,000 times, and take the average across all repetitions to generate the payoffs that a buyer could expect for each combination of bid and signal.

(a) Estimated χ's (b) Subject 38

Figure 11: Panel (a) shows the estimated values of χ_1 and χ_4, omitting 19 subjects with extreme values of one of the parameters. Panel (b) shows the bids and estimated modal choice of subject 38, who had estimated parameters of $\chi_1 = 2.94$ and $\chi_4 = 1.59$.

4.3 Cursed Equilibrium

Motivated by the Winner's Curse in common-value auctions, Eyster and Rabin (2005) propose Cursed Equilibrium as an equilibrium concept. The essence of Cursed Equilibrium is that players correctly interpret their own private information and understand the distribution of other players' actions, but fail to condition on the information that is implied by others' behavior.[21] More specifically, a cursed player incorrectly assigns probability $\chi \in [0, 1]$ to the other players playing their average distribution of actions irrespective of their type rather than their true, type-contingent strategy, to which she assigns probability $1 - \chi$; the parameter χ captures the extent of the bias, with $\chi = 0$ corresponding to the fully rational, Bayesian benchmark, and $\chi = 1$ capturing the fully cursed case where a player assumes no connection between other players' actions and their types.

In our setting, the bidding functions of a cursed player take the following form

$$\begin{aligned} \beta_1(s_i) &= (1-\chi)\,\beta_1(s_i) + \chi E[V|s_i] \\ &= 10\chi + (3.5 - 2.5\chi)\, s_i \end{aligned} \tag{7}$$

for $K = 1$, and

$$\begin{aligned} \beta_4(s_i) &= (1-\chi)\,\beta_4(s_i) + \chi E[V|s_i] \\ &= 7.5 + 2.5\chi + (3.5 - 2.5\chi)\, s_i \end{aligned} \tag{8}$$

[21] "Analogy-Based Expectations Equilibrium" (ABEE; Jehiel, 2005) and "Behavioral Equilibrium" (BE; Esponda, 2008) are equilibrium concepts closely related to cursedness. A fully cursed equilibrium coincides with the coarsest version of ABEE. In our setting, BE predicts *underbidding* for all values of K, and thus cannot explain the overbidding we see empirically.

(a) Estimated 's (b) Subject 96

Figure 12: Panel (a) shows the estimated values of, omitting 4 subjects with estimates of their logit parameters equal to zero. Panel (b) shows the bids and estimated modal choice of subject 96, who had estimated parameter = 0:49.

for $K = 4$. It is worth highlighting that in the fully cursed case, expressions (7) and (8) both reduce to $s_i + 10$; hence a fully cursed buyer would bid the same in both auctions.

We assume that subjects will choose according to the logit stochastic choice function. Thus, we estimate values of and two logit noise parameters, one for each type of auction.[22] Speci cally, we use the same procedure described in Section 4.2 to calculate the “true” payoffs that a buyer should expect to receive for any given bid and signal. We then calculate the “cursed” payoffs as those arising from having the correct beliefs about the likelihood of winning, but believing that the value of winning will always be the signal plus 10. The estimated value of, then, is the weight on the cursed payoffs (with the remaining weight 1 on the true payoffs) that best ts the subjects' choices, given logit errors. We estimate the parameters restricting the values of to be between 0 and 1 (as is generally assumed in models of partial cursedness) and to be weakly greater than zero (so choices are positively correlated with the decision-maker's perceived payoffs).

Panel (a) of Figure 12 shows the results of this estimation process.[23] The vast majority of subjects have estimated values of equal to either zero or one. Panel (b) of the same gure shows the decisions and estimated modal choices of Subject 38, who is the only subject who was classi ed as a cursed decision maker.

[22]Our estimation procedure is different from that used by Eyster and Rabin (2005). It estimates the cursedness parameter based on comparing the best-response function implied by partial cursedness to the empirical distribution of bids. The estimated value of is the one that minimizes the sum of squared deviations between the two. Our procedure allows for a more direct comparison between cursedness and models that are inherently stochastic or that have set-valued best response functions (i.e. QRE and Level-k).

[23]The gure omits four subjects for whom is not identi ed due to the estimated values of $_1$ and $_4$ being zero.

4.4 Level-k Thinking

Level-k Thinking is a structural non-equilibrium model introduced by Stahl and Wilson (1994, 1995) and Nagel (1995) that is meant to capture initial responses to games. Players in these games are assumed to have different levels of reasoning. A “level 0” type doesn't think strategically, choosing an action that seems natural or choosing at random. A “level 1” type assumes all other players are level 0 types and best responds to their beliefs. A “level 2” type assumes all other players are “level 1” and best responds, etc. The level-k model was used in Crawford and Iriberri (2007) to explain overbidding behavior in both private-value and common-value auctions.

To determine behavior predicted by the level-k model, the researcher must make an assumption about the precise behavior of the level 0 type. We follow Crawford and Iriberri (2007) who argue that this basic behavior may take one of two forms: *random* level zero (R0) randomly chooses over the feasible range of bids uniformly without any relation to their private information, while a *truthful* level zero (T0) bids the value that their private information (but not the information conveyed by other buyers' behavior) would imply. We also follow Crawford and Iriberri (2007) in confining our attention to levels 0, 1, and 2, because prior evidence has shown higher levels to be comparatively rare. We summarize the best response behavior for the R0-R2 and L0-L2 types in Table 3.

Types	1-Prize	4-Prize
R0	$U[0;30]$	$U[0;30]$
R1 & T0	$s_i + 10$	$s_i + 10$
R2 & T1	$\begin{cases} 10 & \text{if } s_i \le 4 \\ 15 & \text{if } s_i > 4 \end{cases}$	$\begin{cases} 10 & \text{if } s_i \le 1 \\ 15 & \text{if } s_i > 1 \end{cases}$
T2	$\begin{cases} < 10 & \text{if } s < 2 \\ 10 - 15 & \text{if } 2 \le s \le \frac{1333}{369} \\ > 15 & \text{if } \frac{1333}{369} < s \end{cases}$	$\begin{cases} < 10 & \text{if } s < \frac{512}{369} \\ 10 - 15 & \text{if } \frac{512}{369} \le s \le 3 \\ > 15 & \text{if } 3 < s \end{cases}$

Table 3: Best responses in the level k model

For each subject, we estimate three logit parameters associated with the payoffs from the beliefs of an R1 or L0, an R2 or L1, or an L2 type. We then classify subjects into the category that has the highest log-likelihood. For all subjects that have estimated logit parameters equal to zero for all three types, we classify them as R0. The results of this process can be found in Panel (a) of Figure 13. Almost half of the subjects are classified as being R1 or T0 in both types of auctions, implying that their choices are best explained by beliefs that all other buyers are randomizing uniformly over all possible bids. Furthermore, all seven of the subjects whose overall classification was as a level-k decision maker also fall into this category.

1-Prize \ 4-Prize	R0	R1 & T0	R2 & T1	T2
R0	0 (0)	6 (0)	14 (0)	1 (0)
R1 & T0	3 (0)	51 (7)	17 (0)	2 (0)
R2 & T1	2 (0)	7 (0)	2 (0)	1 (0)
T2	1 (0)	8 (0)	4 (0)	1 (0)

(a) Estimated Types

(b) Subject 109

Figure 13: Panel (a) shows the number of subjects classi ed as each type within each auction. In parentheses, we give the number of subjects whose overall classi cation is level-k who fall into each type. Panel (b) shows the bids and estimated modal choices of subject 109, whose overall classi cation was level-k and whose subtypes were R1 in both auctions.

4.5 Joy of Winning

As our last behavioral model, we consider the Joy of Winning model, which is the one that best describes the majority of our subjects. This model captures the idea that in addition to any monetary payoffs, bidders may directly care about winning the auction. Cox et al. (1988) and Cooper and Fang (2008) found that allowing for such a direct utility of winning was important to explain data from laboratory experiments on private-value auctions. To the best of our knowledge however, with the exception of Van den Bos et al. (2008), previous work has not focused on Joy of Winning as an explanation for overbidding and the Winner's Curse in common-value auctions.

To account for the possibility that subjects may have different feelings about one-prize versus four-prize auctions, we allow the joy gained from winning to vary with each type of auction. We denote the monetary equivalent of the utility from winning a one-prize auction as w_1 and from winning a four-prize auction as w_4. We restrict both joy of winning parameters to be more than zero (so subjects must prefer winning) and less than 25 (the maximum monetary value of winning an auction). We assume that the total utility a subject derives from placing a bid in the one-prize auction is based on the sum of two factors: the probability of winning with that bid multiplied by w_1 and the empirical average of monetary payoffs conditional on making that bid. The total utility from bids in the four-prize auction is calculated in a similar manner.

Finally, we assume that subjects make their choices based on this total utility using a logit stochastic choice model, which includes distinct noise parameters for each type of auction. As a result, we estimate two parameters related to the joy of winning and two logit noise parameters.

(a) Estimated Types

(b) Subject 56

Figure 14: Panel (a) shows the estimated joy of winning parameters, omitting 10 subjects with estimates of their logit parameters equal to zero. Panel (b) shows the bids and estimated modal choices of subject 56, who was classified as a Joy of Winning decision maker and whose joy of winning parameters were 7.3 in the one-prize auction and 2.4 in the four-prize auction.

Panel (a) of Figure 14 shows the results of this estimation procedure. The correlation of w_1 and w_4 among the 110 subjects for whom both are identified is 0.51 (significantly different from 0 with a p-value of less than 0.01). The parameter estimates for subjects classified as behaving according to the Joy of Winning model are presented in blue. These parameters tend to be in one of two clusters. The first cluster has $w_4 = 25$—these are subjects that bid the maximum value in most or all of the four-prize auctions. The second cluster has positive and intermediate values of both w_1 and w_4, with the former being greater than the latter; this is consistent with buyers liking to win both auctions, but having a stronger preference to win when they would be the *unique* winner.

5 Discussion and Conclusion

There is extensive experimental evidence that people systematically overbid in common-value auctions, with subjects often falling prey to the Winner's Curse. Several behavioral models have been proposed to rationalize these findings. However, a perhaps less known prediction of these models is that in common-value auctions with multiple items, bidders should also suffer from a Loser's Curse. In our experiment, which was specifically designed to test for the presence of both curses, we found evidence of the former but not the latter. We also found evidence suggesting that subjects might struggle with contingent thinking. Overall, our results highlight a systematic tendency to overbid, consistent with the Joy of Winning hypothesis; moreover, subjects are prone to various mistakes, such as failing to compute conditional expectations, as suggested by QRE. We conclude the paper with a discussion that places our results in the context of the existing literature; we also discuss some potential limitations of our study as well as possible avenues for future research.

We did not find evidence of the Loser's Curse in our four-prize auctions. This is in contrast to Holt and Sherman (1994), who found evidence for the Loser's Curse under the experimental treatment where it was supposed to arise. However, there are a few differences in our experimental design which might contribute to explain our opposite findings. First, Holt and Sherman (1994) consider a bilateral-trade problem rather than an auction. In their study, buyers, who do not know their valuation but do know it is 1.5 times that of the seller, make a take-it-or-leave-it offer to the seller. Furthermore, in the reported experimental implementation, subjects act as buyers while the seller's behavior is simulated by a computer. Moreover, they interpret their simultaneous finding of both the Winner's Curse and the Loser's Curse (under different experimental conditions) as supporting a model of naïve bidding (which is equivalent to fully cursed equilibrium) over one with a Joy of Winning. In our auction experiment, instead, the results go in the opposite direction; yet, we believe that it is more natural for subjects to experience Joy of Winning when competing in an auction against other humans than when submitting offers to a computerized seller. The empirical differences between our studies suggest that behavior in one setting might not match behavior in the other. Linking behavior across the two settings is a promising avenue for future research.

For our classification exercise in Section 4, we used two distinct empirical approaches. For the purpose of estimating the parameters of QRE, Cursed Equilibrium, and Joy of Winning, we first used the empirical distribution of bids to compute buyers' expected monetary payoffs, and then used those payoffs to estimate the behavioral parameters. This contrasts with the approach we used for Level-k thinking, where we made specific assumptions about what buyers of different levels believe their payoffs would be, and then estimated the levels based on these beliefs.[24] It is possible that the estimated parameters might be different if the empirical distribution of payoffs played a role in subjects' hypothesized beliefs.

While behavior in our study was closer to the rational benchmark in the valuation task than in the auctions, subjects' choices in the former setting still displayed a clear tendency to overbid. Indeed, despite the effects of rank information found in Table 1 following the correct order (the effect for the highest signal is the most negative, followed by the second-highest signal, etc.), they are not fully distinguishable statistically, and are quite far from the rational prediction. Moreover, the estimated responsiveness of valuations to the signal conditional on rank information is not statistically distinguishable from one, and thus much lower than the rational benchmark of three. We believe that subjects' inability to correctly compute conditional expectations is likely to have an important

[24] Camerer et al. (2016) use the same approach of relying on empirical payoff distributions for QRE and Cursed Equilibrium while using the theoretical payoffs for Level-k. Goeree et al. (2016) refer to the use of the empirical distribution of bids as the “empirical payoff approach”, as compared to the “equilibrium correspondence approach” of relying solely on theoretical assumptions about payoffs.

effect across many economic settings, as noted also by Nagel et al. (2024); hence, it should probably be accounted for before proposing other, more complicated behavioral mechanisms.

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Appendix

A Online Appendix: Additional Empirical Results

A.1 Additional Tables & Figures

Table 4: Summary Statistics

	Mean	Std. Dev.
CRT Score	1.53	1.18
Female	0.59	0.49
Age	23.43	4.79
English	0.23	0.42
Economics	0.33	0.47
Subjects	120.00	

Notes: CRT Score is the number of correct answers on a Cognitive Re ection Test, ranging from 0 to 3. Female, English, and Economics are equal to one if the subjects report being female, speaking English as a rst language, and majoring in Economics, respectively.

Table 5: Choices

	(1) Choice	(2) Choice
Four-Prize	1.58	0.77
	(0.55)	(0.56)
Reservation	-0.74	-1.25
	(0.50)	(0.49)
Experienced Four-Prize		1.62
		(0.38)
Experienced Reservation		1.02
		(0.48)
Constant	15.3	15.3
	(0.29)	(0.29)
Observations	7200	7200

Notes: Linear regression with subject-round xed effects and standard errors clustered at the subject level. Signi -cance indicated by: *** $p \leq 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 15: Average Value vs. Theory – Lowest Signal

Figure 16: Average Value vs. Theory – Fourth-Highest Signal

Figure 17: Average Value vs. Theory – Third-Highest Signal

Figure 18: Average Value vs. Theory – Second-Highest Signal

Figure 19: Average Value vs. Theory – Highest Signal

Table 6: Choices

	(1) Choice	(2) Choice	(3) Choice	(4) Choice	(5) Choice	(6) Choice
One-Prize (Highest Signal)	1.60					1.60
	(0.56)					(0.56)
Four-Prize (Highest Signal)	3.09					3.09
	(0.69)					(0.69)
One-Prize (Second Highest Signal)		1.34				1.34
		(0.60)				(0.60)
Four-Prize (Second Highest Signal)		2.37				2.37
		(0.70)				(0.70)
One-Prize (Third Highest Signal)			0.15			0.15
			(0.60)			(0.60)
Four-Prize (Third Highest Signal)			2.19			2.19
			(0.66)			(0.66)
One-Prize (Fourth Highest Signal)				0.57		0.57
				(0.74)		(0.74)
Four-Prize (Fourth Highest Signal)				2.18		2.18
				(0.76)		(0.76)
One-Prize (Lowest Signal)					0.051	0.051
					(0.59)	(0.59)
Four-Prize (Lowest Signal)					1.76	1.76
					(0.57)	(0.57)
Constant	14.9	14.7	15.0	14.1	14.0	14.5
	(0.37)	(0.38)	(0.35)	(0.44)	(0.34)	(0.31)
Observations	1440	1440	1440	1440	1440	7200

Notes:Linear regression with subject-round xed effects and standard errors clustered at the subject level. Signi - cance indicated by: *** $p \le 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Bidding and Subject Understanding

	(1) One-Prize-Bid	(2) One-Prize-Bid	(3) Four-Prize-Bid	(4) Four-Prize-Bid
Signal	0.67	0.52	0.67	0.58
	(0.19)	(0.13)	(0.14)	(0.11)
High Quiz Score Signal	0.15		-0.041	
	(0.21)		(0.17)	
High CRT Signal		0.48		0.13
		(0.18)		(0.16)
Constant	13.4	13.4	15.3	15.3
	(0.22)	(0.22)	(0.19)	(0.19)
Observations	2400	2400	2400	2400

Notes: Linear regression with subject- and round- xed effects and standard errors clustered at the subject level. Signi cance indicated by: *** p< 0.01, ** p< 0.05, * p< 0.1. “High Quiz Score” is equal to one if the subject got at least six out of the seven quiz questions correct. “High CRT” is equal to one if the subject got at least 2 out of the three CRT questions correct.

Table 8: Valuations and Subject Understanding

	(1) Reservation Price	(2) Reservation Price	(3) Reservation Price
Signal	1.33	1.65	1.22
	(0.20)	(0.25)	(0.17)
Highest Signal	-3.85	-4.65	-2.74
	(0.84)	(0.88)	(0.76)
Second Highest Signal	-2.88	-3.26	-1.78
	(0.74)	(0.85)	(0.69)
Third Highest Signal	-1.73	-2.15	-0.81
	(0.61)	(0.71)	(0.60)
Fourth Highest Signal	-1.52	-1.76	-0.67
	(0.54)	(0.56)	(0.54)
Constant	12.8	12.2	12.7
	(0.32)	(0.29)	(0.34)
High Quiz Score	Yes	No	No
High CRT	No	Yes	No
Observations	1740	1280	2400

Notes: Linear regression with subject- and round- xed effects and standard errors clustered at the subject level. Signi cance indicated by: *** p< 0.01, ** p< 0.05, * p< 0.1. Column (1) only includes data from subjects that got at least six out of the seven quiz questions correct. Column (2) only includes data from subjects that got at least 2 out of the three CRT questions correct. Column (3) duplicates the results from Table 1 and is included for comparison.

(a) One-Prize (b) Four-Prize

Figure 20: Averages vs. Quantal Response Equilibrium

A.2 QRE

In this section, we present the results of calculating the distribution of bids under a Logistic Quantal Response Equilibrium (QRE) for various QRE parameters across different types of auctions. The computation of these probabilities is performed iteratively.

For each value of , we start by setting the bidding probabilities uniformly across all bids for each signal.[25] Assuming all players follow this initial distribution, we calculate the expected payoff for each possible bid. We then update the bidding probabilities by incorporating the expected payoffs and into the logit choice probabilities. This process continues until the bidding distribution stabilizes at a xed point.

Figure 20 shows the average bidding functions generated by QRE equilibria for various values of . the empirical average of bidding in the one-prize auctions is higher than QRE's predicted average for almost all signals and values of , with the closest match being $= 0.1$. For four-prize auctions, average bidding under $= 0.5$ matches many of the broad patterns of average empirical bids.

B Online Appendix: AICs

Below, we report the AICs for each model.

[25] Due to computational limitations, we restrict bids to dollar values instead of using increments of $0.20 as in the actual experiment.

Subject	QRE	Cursedness	Level k	Joy of Winning
1	393.926	395.821	396.902	370.035
2	399.261	400.982	407.93	401.872
3	389.407	389.426	389.02	391.187
4	383.965	385.625	386.565	380.628
5	401.386	403.385	403.685	391.238
6	404.637	406.637	404.178	246.64
7	399.056	400.584	402.632	392.909
8	362.608	364.033	351.552	366.541
9	388.44	389.426	391.622	388.865
10	403.149	405.149	399.115	328.826
11	402.295	404.295	406.956	383.122
12	390.828	392.771	392.692	346.473
13	393.137	394.994	400.689	396.671
14	400.751	402.751	400.65	332.394
15	397.483	399.006	402.963	401.405
16	400.984	402.984	406.661	404.841
17	380.141	381.25	380.336	375.308
18	340.203	334.31	328.54	335.231
19	386.578	388.313	391.503	387.186
20	404.279	406.279	408.979	359.617
21	402.561	404.561	408.143	389.254
22	404.401	406.401	409.467	396.571
23	387.351	389.29	391.828	390.98
24	396.808	398.808	398.677	344.599
25	405.082	407.082	409.147	373.087
26	398.172	399.84	408.107	359.328
27	375.775	376.805	376.621	350.613
28	366.245	363.615	366.699	341.07
29	388.848	389.317	397.142	389.178
30	397.127	398.359	403.85	393.302

Subject	QRE	Cursedness	Level k	Joy of Winning
31	361.54	360.036	372.07	351.623
32	394.003	395.817	398.81	397.107
33	385.675	387.675	393.633	380.621
34	400.481	402.481	405.397	378.216
35	384.946	386.703	387.255	383.773
36	377.904	379.608	383.612	376.663
37	360.84	359.687	357.622	361.012
38	372.014	373.705	379.858	372.195
39	405.382	407.382	411.375	409.346
40	399.75	401.723	406.08	395.563
41	404.705	406.705	407.659	377.573
42	393.788	395.788	394.778	378.006
43	404.487	406.487	400.694	350.134
44	393.257	394.696	392.098	381.816
45	382.537	381.371	389.02	377.582
46	401.044	403.044	405.911	396.545
47	393.17	395.17	401.58	395.967
48	399.127	401.127	408.607	403.028
49	404.228	406.134	411.558	408.228
50	377.111	378.287	377.196	374.242
51	342.259	343.988	359.502	342.092
52	356.758	358.758	360.827	358.592
53	392.575	393.899	391.987	371.169
54	399.621	401.621	401.553	365.403
55	402.716	404.716	406.346	342.378
56	394.719	396.059	392.03	341.549
57	400.866	402.848	402.531	396.792
58	402.138	404.138	398.19	381
59	373.474	301.336	298.962	287.391
60	392.358	394.17	393.845	377.439

Subject	QRE	Cursedness	Level k	Joy of Winning
61	400.564	402.565	387.253	365.672
62	306.421	308.421	331.039	310.421
63	387.513	389.329	388.721	382.6
64	402.855	404.855	403.472	376.391
65	390.42	392.42	389.62	364.665
66	405.382	407.382	412.385	407.995
67	399.909	401.909	405.062	403.909
68	404.717	406.717	406.211	324.157
69	376.91	378.91	393.289	380.91
70	360.558	361.561	359.707	334.295
71	373.351	372.973	361.131	324.003
72	392.832	394.832	401.492	396.832
73	395.751	397.628	400.223	395.948
74	390.076	392.076	391.23	377.775
75	390.911	392.408	404.349	374.438
76	401.014	403.014	403.17	350.96
77	354.348	305.382	289.406	303.515
78	362.447	361.303	363.936	360.447
79	393.634	394.92	396.538	381.235
80	403.865	405.837	410.749	404.117
81	402.472	404.472	397.567	380.169
82	403.026	404.97	403.584	376.014
83	386.708	387.358	377.823	323.886
84	368.94	370.492	369.233	372.913
85	402.548	404.491	407.535	399.803
86	400.45	402.183	406.001	403.983
87	384.497	385.963	385.238	378.781
88	376.951	378.29	374.283	341.433
89	405.382	407.382	407.007	406.252
90	394.674	396.35	391.886	345.908

Subject	QRE	Cursedness	Level k	Joy of Winning
91	366.315	368.315	373.293	365.465
92	385.725	386.792	384.793	347.679
93	342.391	341.442	323.951	332.374
94	374.592	376.592	384.431	378.592
95	398.291	399.85	398.23	383.321
96	306.383	298.964	299.445	305.207
97	403.391	405.391	398.917	356.49
98	403.491	405.491	407.169	365.471
99	400.732	402.732	398.697	382.393
100	398.797	400.797	403.481	369.519
101	379.092	381.092	392.987	383.092
102	374.962	375.214	371.1	366.537
103	395.69	397.589	401.041	373.995
104	397.976	399.634	394.075	350.601
105	405.382	407.382	410.769	221.358
106	402.605	404.605	401.091	379.269
107	395.43	397.43	399.022	383.331
108	402.046	403.744	407.573	373.113
109	331.331	300.613	284.171	326.659
110	389.302	391.194	387.889	366.984
111	400.805	402.805	403.328	368.872
112	400.949	402.859	402.45	378.697
113	387.187	388.251	387.843	388.318
114	359.395	361.395	368.313	359.988
115	366.761	367.914	368.648	370.761
116	386.931	388.686	394.165	389.784
117	364.91	366.409	382.254	367.997
118	387.105	388.481	390.471	384.405
119	379.111	380.554	370.061	365.31
120	404.049	406.049	404.212	397.392

C Online Appendix: Experimental Screenshots

Below, we include screenshots from the experiment.

Figure 21: Introduction

Figure 22: Basic Instructions

Figure 23: Instructions: Bidding Stage

Figure 24: Instructions: Purchase Stage

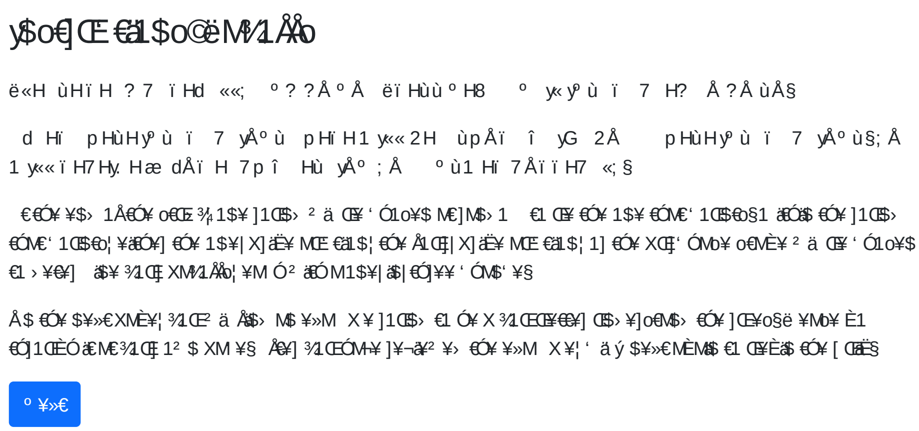

Figure 25: Instructions: Payoffs

Example

PLEASE READ THE EXAMPLE CAREFULLY AND CLICK NEXT WHEN YOU ARE READY TO BEGIN THE QUIZ.

The table below shows an example of the players' (A, B, C, D, and E) signals and decisions in each task.

Player	Signal	One-Prize Auction Bid	Four-Prize Auction Bid	Purchase Stage Choice
A	\$1.40	\$4.80	\$9.00	\$3.40
B	\$0.80	\$3.60	\$3.80	\$2.80
C	\$4.00	\$23.00	\$12.40	\$20.00
D	\$1.40	\$9.20	\$9.60	\$6.40
E	\$3.40	\$9.00	\$8.20	\$9.80

In this example, the value of the prize (for all players and every decision) is: \$1.40+\$0.80+\$4.00+\$1.40+\$3.40=\$11.

In the **one-prize auction**, Player C is the winner as she bid the highest; hence, she gets the prize and pays \$9.20 for it, as this was the value of the second-highest bid. Player C's payoff from this auction is \$30+\$11-\$9.20=\$31.80, while all other players' payoffs are \$30.

In the **four-prize auction**, Players A, C, D and E are the four highest bidders; hence, they each get the prize and pay \$3.80 for it, as this was the value of the lowest bid. The four winners' payoffs are \$30+\$11-\$3.80=\$37.20, while Player B's payoff is \$30.

For the **purchase stage**, suppose that the randomly drawn price is \$4. Consider first Player B who was told that she had the lowest signal and indicated that she was willing to purchase the prize at any price lower than or equal to \$2.80. In this case, given that the randomly drawn price is higher than her maximum purchase price, she would not purchase the prize and she would receive a payoff of \$30. Next, consider Player E who was told that he had the second-highest signal and indicated that he was willing to purchase the prize at any price lower than or equal to \$9.80. In this case, given that the randomly drawn price is lower than his maximum purchase price, he would purchase the prize at a price of \$4 and he would receive a payoff of \$30+\$11-\$4=\$37.

Next

Figure 26: Example

Quiz

You will now be given a series of questions to check your understanding of the instructions and examples. You will be paid $1 for each answer you get correct.

Suppose that your signal is $2.2, and the other four signals are $1.6, $3.4, $4.8, and $5. What is the value of the prize?

- $11
- $13
- $15
- $17

How many players are in each group?

- Two.
- Three.
- Four.
- Five.

Suppose that in the one-prize auction, you bid $8 and the other bids are $4, $5, $11, and $12. What is true about the outcome?

- You win a prize. The price in the auction is $11.
- You win a prize. The prize in the auction is $4.
- You do not win a prize. The price in the auction is $11.
- You do not win a prize. The price in the auction is $4.

Suppose that in the four-prize auction, you bid $8 and the other bids are $4, $5, $11, and $12. What is true about the outcome?

- You win a prize. The price in the auction is $11.
- You win a prize. The prize in the auction is $4.
- You do not win a prize. The price in the auction is $11.
- You do not win a prize. The price in the auction is $4.

Suppose that in the one-prize auction, you bid $12 and the other bids are $5, $6, $10, and $16. What is true about the outcome?

- You win a prize. The price in the auction is $12.
- You win a prize. The price in the auction is $5.
- You do not win a prize. The price in the auction is $12.
- You do not win a prize. The price in the auction is $5.

What is true about how the price is determined in the purchase stage?

- The price that is selected will be higher if the value of the prize is higher.
- Each possible value of the price is equally likely to be chosen.
- Another player will choose your price.
- The price is determined by the outcome of the four-prize auction.

What is true about the how prizes are distributed in the purchase stage?

- Either everyone wins the prize, or no one does.
- One player in each group will win a prize.
- Four players in each group will win a prize.
- Other players' choices do not affect your chances to receive a prize.

When you believe you have answered all questions correctly, press next to check your answers.

Next

Figure 27: Quiz

Quiz Answers

The answers for the quiz are given below. Please review the answers and note any mistakes you have made.

Question 1: Suppose that your signal is $2.2, and the other four signals are $1.6, $3.4, $4.8, and $5. What is the value of the prize?
Correct Answer: $17
Your Answer: $15

Question 2: How many players are in each group?
Correct Answer: Five.
Your Answer: Four.

Question 3: Suppose that in the one-prize auction, you bid $8 and the other bids are $4, $5, $11, and $12. What is true about the outcome?
Correct Answer: You do not win a prize. The price in the auction is $11.
Your Answer: You do not win a prize. The price in the auction is $11.

Question 4: Suppose that in the four-prize auction, you bid $8 and the other bids are $4, $5, $11, and $12. What is true about the outcome?
Correct Answer: You win a prize. The prize in the auction is $4.
Your Answer: You do not win a prize. The price in the auction is $11.

Question 5: Suppose that in the one-prize auction, you bid $12 and the other bids are $5, $6, $10, and $16. What is true about the outcome?
Correct Answer: You do not win a prize. The price in the auction is $12.
Your Answer: You do not win a prize. The price in the auction is $12.

Question 6: What is true about how the price is determined in the purchase stage?
Correct Answer: Each possible value of the price is equally likely to be chosen.
Your Answer: Another player will choose your price.

Question 7: What is true about the how prizes are distributed in the purchase stage?
Correct Answer: Other players' choices do not affect your chances to receive a prize.
Your Answer: Four players in each group will win a prize.

You earned $2.0 from your correct answers. Please review any questions you answered incorrectly. When you are ready to begin the first round, click the next button.

Next

Figure 28: Quiz Answers

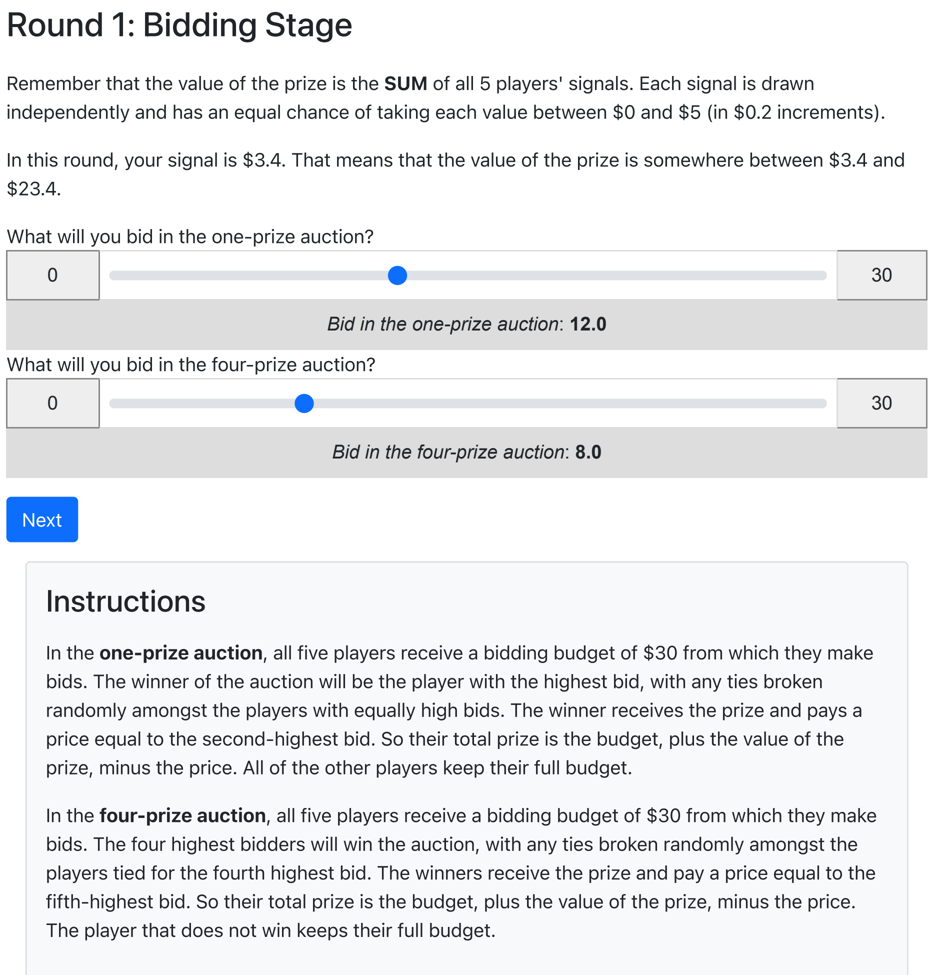

Figure 29: Bidding Stage

Round 1: Purchase Stage

Remember that the value of the prize is the **SUM** of all 5 players' signals. Each signal is drawn independently and has an equal chance of taking each value between $0 and $5 (in $0.2 increments).

In this round, your signal is $3.4. That means that the value of the prize is somewhere between $3.4 and $23.4.

We can also inform you that I I . That means that one player in your group has a signal that is greater than or equal to yours and three players in your group have signals that are less than or equal to yours.

What is the maximum price at which you would purchase the prize?

0 30

Maximum price at which you will buy: 17.2

Next

You will be asked for the maximum price at which you would be willing to purchase the prize. After you choose your maximum price, a random price will be drawn and compared to your maximum price. If the randomly drawn price is (weakly) lower than your maximum price, then you will purchase a prize at the randomly drawn price out of your budget of $30. Otherwise you will keep your full budget of $30, but will not receive a prize.

The price that you end up facing will be chosen randomly between $0.20 and $30, with each multiple of $0.20 being equally likely to be drawn. Your choices cannot affect the price. Therefore, it is in your best interest to answer each question as if you were facing that price with certainty.

Price	Purchase?	Price	Purchase?	Price	Purchase?	Price	Purchase?	Price	Purchase?	Price	Purchase?
$0.20		$5.20		$10.20		$15.20		$20.20		$25.20	
$0.40		$5.40		$10.40		$15.40		$20.40		$25.40	
$0.60		$5.60		$10.60		$15.60		$20.60		$25.60	
$0.80		$5.80		$10.80		$15.80		$20.80		$25.80	
$1.00		$6.00		$11.00		$16.00		$21.00		$26.00	
$1.20		$6.20		$11.20		$16.20		$21.20		$26.20	
$1.40		$6.40		$11.40		$16.40		$21.40		$26.40	
$1.60		$6.60		$11.60		$16.60		$21.60		$26.60	
$1.80		$6.80		$11.80		$16.80		$21.80		$26.80	
$2.00		$7.00		$12.00		$17.00		$22.00		$27.00	
$2.20		$7.20		$12.20		$17.20		$22.20		$27.20	
$2.40		$7.40		$12.40		$17.40		$22.40		$27.40	
$2.60		$7.60		$12.60		$17.60		$22.60		$27.60	
$2.80		$7.80		$12.80		$17.80		$22.80		$27.80	
$3.00		$8.00		$13.00		$18.00		$23.00		$28.00	
$3.20		$8.20		$13.20		$18.20		$23.20		$28.20	
$3.40		$8.40		$13.40		$18.40		$23.40		$28.40	
$3.60		$8.60		$13.60		$18.60		$23.60		$28.60	
$3.80		$8.80		$13.80		$18.80		$23.80		$28.80	
$4.00		$9.00		$14.00		$19.00		$24.00		$29.00	
$4.20		$9.20		$14.20		$19.20		$24.20		$29.20	
$4.40		$9.40		$14.40		$19.40		$24.40		$29.40	
$4.60		$9.60		$14.60		$19.60		$24.60		$29.60	
$4.80		$9.80		$14.80		$19.80		$24.80		$29.80	
$5.00		$10.00		$15.00		$20.00		$25.00		$30.00	

Figure 30: Purchase Stage

Figure 31: Results