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Opportunity Cost, Inattention and the Bidder's Curse

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Opportunity cost, inattention and the bidder's curse *

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Abstract

Auction winners sometimes suffer a "bidder's curse", paying more for an item at auction than the fixed price charged for an identical item by other sellers. This seemingly irrational behavior is puzzling because the information necessary to avoid overpaying would appear to be readily available to bidders, yet they seem to ignore it. To understand this behavior, we consider the bidders' decisions whether to acquire information about the fixed price before bidding, in the presence of opportunity costs. Our theory introduces costly information acquisition into an auction model, with a fixed price aftermarket selling an identical good. When information about the fixed price is costly, bidders sometimes remain rationally ignorant and overbid in the auction, generating the bidder's curse. To assess the empirical validity of our proposed explanation, we study the model's predictions in an experiment where subjects have an opportunity cost of looking up a fixed price and bid in an auction. We find that information acquisition decreases and overbidding increases with opportunity cost as predicted. Most observed lookup behavior is rationalizable and rational ignorance reliably generates the bidder's curse.

JEL classification: C72, C92, D44

Keywords: Auctions, Bidder's Curse, Limited Attention, Experiments, Rational Ignorance

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There is no 'imperfection' in a market possessing incomplete knowledge if it would not be remunerative to acquire (produce) complete knowledge: information costs are the costs of transportation from ignorance to omniscience, and seldom can a trader afford to take the entire trip. ∼ George Stigler (1967)

1 Introduction

Overbidding in auctions has been observed in a wide range of scenarios ranging from private-value second-price auctions to common-value auctions of many formats in both the lab and the field (Kagel et al., 1987; Kagel and Levin, 1993; Cooper and Fang, 2008; Kagel and Levin, 1986; Klemperer, 2002; Levin and Reiss, 2017). These pathological cases frequently result in the winner of the auction paying more for the item than it is actually worth. A different form of overbidding, termed the "bidder's curse" by Malmendier and Lee (2011), has been documented among eBay bidders who sometimes overpay in auctions relative to a simultaneously available fixed-price (see also Jones, 2011).

Bidders subject to the bidder's curse fail to maximize their gains from exchange, and the proffered explanation for this seemingly irrational behavior is that bidders "fail to pay sufficient attention to their outside options, especially when rebidding" (Malmendier and Lee, 2011, p. 776). Two possible explanations for *why* individuals fail to pay 'sufficient' attention have been advanced. Malmendier and Lee (2011) suggest that the source of limited attention is non-rational, and Schneider (2016) suggests that some overbidding might be explained as a rational response to search costs – rational ignorance.[1] Both elements likely contribute to the bidder's curse, but the purpose of our paper is to show how rational ignorance can generate behavior that looks like the bidder's curse but is in fact rational. Specifically we focus on incentives created by the time and effort cost of researching the fixed price, which we will refer to as the opportunity cost of information, and which is typically abstracted away in the auction literature. In the case of eBay auctions, some bidders may find occupying themselves with the search for alternative offers is the best thing to do, due to negligible opportunity costs, while others may be more reluctant to spend time searching. Hence, opportunity costs of researching alternative prices seem to be quite heterogeneous across bidders in real life. In field data, the opportunity costs of information are uncontrolled and difficult to observe. To address this limitation, we

[1] Note that the former is a species of "behavioral inattention" as described by Gabaix (2019), but the latter is conceptually distinct from "rational inattention" (e.g. Sims, 2003). Rational ignorance has often been studied in the context of voting behavior (see e.g. Martinelli, 2007).

design a laboratory experiment to directly test whether rational ignorance, driven by the opportunity cost of looking up a fixed price, can account for the bidder's curse.[2]

The bidder's curse can only arise among auction participants, and only when the item at auction is also available from another seller at a fixed price. Thus we begin with a set of bidders who have already discovered the auction and for whom all costs related to identifying this opportunity are sunk. In practice, these bidders may differ in what they know about substitute goods available elsewhere. Some bidders may have researched a fixed price before entering, others may be uninformed about it and instead form an expectation about it. It is also conceivable that bidders are completely unaware of the existence of substitutes. For such bidders, explaining the bidder's curse is a no-brainer: in an ascending auction these bidders simply bid their valuation which may exceed the fixed price. Our focus is on explaining the bidder's curse even among those who are aware of the existence of substitutes. While a bidder's curse among these bidders could have irrational origins, we show that it can also arise among fully rational – but uninformed – bidders who face opportunity costs of researching substitutes.

To see how heterogeneous opportunity costs can matter, consider an eBay bidder who enters an auction to buy some desired item while sitting at home on a Sunday afternoon. At some point that bidder may receive a notification from eBay that she has been outbid, and she will have to decide whether to increase her bid. In a frictionless environment, the optimal bid depends on the buyer's value and on the price of available substitutes. Thus the decision of whether to bid (and how much) involves a simple calculation. But there is no such thing as a frictionless environment. Given the nature of eBay auctions, the timing of that notification and the timeframe available for the bidder to respond may vary. Learning about the price of available substitutes may be costly, and the cost will depend on generally unobservable characteristics of the bidder. Mid-afternoon on a Wednesday, researching the price of a video game or baby clothes may cost an office worker an important contract (or even their job), but for someone working the night shift, or staying home with the kids, that might well be their leisure time (or the kids' nap time) rendering the costs of researching prices much lower.

More generally, regarding opportunity costs, auctions are conducted on the schedule of the seller and often have a hard close. This naturally generates heterogeneity in opportunity costs of researching substitutes during the auction. By contrast, unsuccessful

[2] Though we were unaware of this when we began our study, this implements a laboratory test suggested by Malmendier (2016, p. 1203-4) that uses exogenous variation in "search costs" to test whether such costs can explain the bidder's curse.

bidders can choose when to enter the aftermarket to research substitutes and buy at a fixed price, allowing them to act at a time that minimizes their opportunity costs.

We develop a simple model of this kind of problem and show that, depending on the opportunity cost of acquiring information, "the bidder's curse" can sometimes arise as a consequence of the rational decision to submit a bid while nevertheless remaining uninformed about the price of alternatives. Then we show that such behavior varies predictably in a laboratory implementation of our model.

In our setting, subjects participate in a sequence of induced private value, ascending clock auctions for goods that are subsequently available for purchase at a fixed price drawn from a known distribution.[3] Each subject demands a single unit and, for simplicity, values the unit sufficiently that she will strictly prefer to purchase at the fixed price if she is unsuccessful in the auction. To learn the actual fixed price before bidding, subjects must forgo the opportunity to earn money in an individual effort task. Thus in deciding whether to research the fixed price, subjects face a tradeoff between this opportunity cost and the expected savings from making an informed bid.

We provide a benchmark theoretical model in which rational ignorance is an equilibrium outcome when the opportunity cost of becoming informed is sufficiently high. In the model, rational ignorance generates behavior consistent with the bidder's curse because uninformed agents sometimes bid above the fixed price. By varying the piece rate of our experimental effort task, our design allows us to observe the information acquisition strategies of subjects with varying opportunity costs and their bidding behavior conditional on whether they have observed the fixed price. By comparing across treatments, we are able to identify how much of total overbidding is driven by rational ignorance, as opposed to other behavioral factors.

As predicted, we find evidence that buyers who face higher opportunity costs of learning the fixed price are less likely to learn, and hence more likely to overbid, the fixed price. However, when the opportunity cost of researching the fixed price is high, auction winners who choose *not* to research the fixed price receive significantly higher payoffs than those who *do* since their earnings from the effort task more than offset their occasional losses from overbidding. Our analysis shows that opportunity cost-driven overbidding is not harmful on net.

Existing field studies offer suggestive evidence to support theoretical claims that opportunity cost plays an important role in bidding behavior (e.g. Backus et al., 2014;

[3] For a discussion of these "English clock" auctions, see Cassady (1980); McCabe et al. (1990).

Schneider, 2016), albeit without observing or controlling opportunity cost. In laboratory auctions in which the item is alternatively available at a fixed price any time until the auction starts, Durham et al. (2013) observe bids in excess of the fixed price in only 4 out of 359 observations, suggesting that limited attention is a weak constraint in a zero-opportunity cost environment.[4] Other evidence from internet auctions suggests a role for more careful attention to quasi-rational explanations as opposed to behavioral biases (e.g. Podwol and Schneider, 2016).[5]

Suppose an analyst was given access to our bid and fixed price data but was unaware of the existence of variation in the cost of acquiring information about the fixed price. They would observe clear evidence of the bidder's curse and might be drawn to explain it in terms of irrational motivation. However, with knowledge of this source of heterogeneity, the observed bids and prices are much less puzzling (despite the existence of some residual overbidding that is not neatly explained by the model). The laboratory allows us to cleanly highlight how a particular kind of usually unobserved heterogeneity can generate a particular kind of seemingly irrational overbidding, but the broader implication is that unobserved heterogeneity can confound inference from observed behavior to irrational motivation.

2 Theory

We construct a simple model, suitable for experimental study, in which a bidder's opportunity cost of looking up a fixed price can influence their price lookup and bidding decisions. In our setting there are $n \geq 2$ players, who each demand a single unit of a good. The good is sold in both a second-price ascending clock auction and an aftermarket. One unit of the good is available in the auction, but an unlimited quantity of the good is available in an aftermarket at a fixed price. The aftermarket price, q, is not initially observed by players, but is commonly known to be drawn from cumulative distribution function G which admits a probability density function and has support on $[\underline{q}, \overline{q}]$ where

[4] Data on overbidding collected via personal communication with the authors.

[5] We note in passing that leading explanations for the simultaneous use of fixed prices and auctions, as well as the use of "Buy-it-Now" prices in eBay auctions are based on buyers' and sellers' costs of delay (Gallien and Gupta, 2007; Caldentey and Vulcano, 2007; Hummel, 2015), and bidders' risk aversion (Reynolds and Wooders, 2009). Shahriar and Wooders (2011) provide experimental evidence on how bidders behave in auctions with buy-it-now prices and Ackerberg et al. (2017) provide an empirical analysis of the two aforementioned explanations of the use of buy-it-now prices on eBay. Vadovič (2017) theoretically studies eBay bidders who can search for a fixed price alternatives before or during bidding.

$\underline{q} \geq 0$.[6] A given player i values one unit of the good at v_i, which she privately observes, but v_i is commonly known to satisfy $v_i \geq \overline{q}$.[7]

Each player first bids in the auction, and if she does not win the auction, she can instead buy the good in the aftermarket. We normalize the cost of participating in the aftermarket to zero, because we assume that buyers can optimally choose when to buy in the aftermarket to minimize opportunity costs. However, each player may choose to privately observe the aftermarket price before the auction starts at a cost. In particular, looking up the price requires forgoing a task with individual reward, c_i. Before she decides whether to lookup the fixed price, this reward is privately observed by i and is known to be drawn independently according to the cumulative distribution function F. A player's lookup decision is also her private information.

Our environment is designed to capture important features of the situation faced by an eBay bidder who has recently been outbid and must choose whether to continue to increase her bid.[8] When eBay bidders are outbid, they receive a notification by email that they are no longer the high bidder. They then must choose whether to increase their bid and also whether to devote some of their valuable time to researching other purchase options (like eBay's Buy-It-Now price, or fixed price options from other sellers, which are equivalent to our aftermarket price).[9] Here we ask whether it is ever rational *ex ante* to overbid these fixed price options, and we show that when the opportunity cost of research is sufficiently high, some bidders will remain uninformed about, and overbid relative to, the fixed price.

Our model is related to Vadovič (2017), who studies the timing of bids in a dynamic model of internet auctions with two rounds of bidding separated by an opportunity to research a fixed price. In that model, a bidder's curse could arise because bidders with

[6] It is possible to interpret q as the sum of the aftermarket price plus any fixed costs of entering the aftermarket common to all buyers.

[7] It is straightforward to extend the model to incorporate a fraction β of the population who have value $v_i < \underline{q}$, while remaining bidders have values with $v_i \geq \underline{q}$. We obtain more complicated expressions but the same overall insights from that extended model. Since these bargain hunters with $v_i < \underline{q}$ will always bid below q, the first-order effect of raising β is to reduce the prevalence of the bidder's curse, although this effect is attenuated by reducing incentives for the other buyers both to acquire information and to bid-shade to avoid the bidder's curse.

[8] Ariely et al. (2005) and Roth and Ockenfels (2002) argue that second-price auctions can be considered stylized versions of those run at eBay, where initial data on overbidding fixed price options was collected. See Ambrus et al. (2018) and Hopenhayn and Saeedi (2016) for recent work on dynamic bidding behavior that can occur in richer models of eBay auctions.

[9] For simplicity, we assume that all bidders enter the auction uninformed about the price of these substitutes. Including a mass of already informed bidders complicates the analysis without altering the basic implications.

high search costs have incentive to submit high bids early, signaling their search costs via commitment to buying in the auction, and forgoing the chance to research the fixed price.[10] Because we abstract from the timing of bids and signaling motives, we can focus on the direct connection between information acquisition decisions and bidding behavior.

2.1 Preview of the Analysis

Formally, a strategy for player i prescribes her information acquisition as a function of her realized v_i and c_i; the price at which she drops out of the ascending auction (her bid) conditional on her information acquisition, v_i, and c_i; and her decision of whether or not to acquire the good in the aftermarket conditional on losing the auction and on v_i, c_i, her information acquisition, and her bid.

Below, we assume that all players are risk neutral and construct an essentially unique symmetric perfect Bayesian equilibrium (PBE) of this game.[11] This PBE is described by an information acquisition function ι and an uninformed bid $b^\star$ such that each player follows the strategy given by (A)-(D) below:

(A) Each player acquires information with probability $\iota(c_i)$ when her type is (v_i, c_i).

(B) Each player, conditional on becoming informed that the aftermarket price is q, bids q in the auction.

(C) Each player, conditional on remaining uninformed, bids $b^\star$ in the auction.

(D) All types always buy in the aftermarket conditional on losing the auction.

Characterizing a PBE involves finding the restrictions on ι and $b^\star$ that make the strategies described by (A)-(D) consistent with PBE. We construct the PBE by first finding the optimal bid of a player, given her information about the aftermarket price and conditional on the information acquisition strategies of others. We then characterize the value of information and derive a subject's information acquisition strategy. In the PBE, agents acquire information according to a cutoff strategy in opportunity cost, becoming informed only when the expected value of being informed exceeds the opportunity cost of

[10]In addition to studying a dynamic auction, the setup differs from ours because fixed prices are independent across bidders, and a bidder can only buy at a fixed price after the auction if they chose to look it up during the auction.

[11]The equilibrium is essentially unique in the sense that in every symmetric PBE, bidders play according to the PBE strategies we derive with probability 1 – see Lemmas 2 and 4 in Appendix A, where we formally derive the PBE.

acquiring information. Then given their information, agents bid either their conditional-on-winning expectation of the aftermarket price (if uninformed) or the actual aftermarket price (if informed). When some bidders are uninformed, this equilibrium may generate both over- and under-bidding in the auction stage, relative to the aftermarket price. Thus, with positive opportunity costs of information acquisition, rationally ignorant bidders exhibit behavior that looks like the "bidder's curse".

2.2 Bidding strategies conditional on information

A player's optimal bid in the auction depends on whether she is informed about the aftermarket price, q. Note that since $v_i \geq \overline{q} \; \forall \, i$, players will always prefer to purchase the good at a price q in the aftermarket if they do not buy during the auction. Thus, for an *informed* player, a bid of q in the auction weakly dominates all other bids. Bidding q both ensures that the player will never overpay relative to the aftermarket price and maximizes the probability of winning the item at a price below q, should other players underbid. Since the price paid by the auction winner is unaffected by her own bid, it follows that this strategy minimizes her expected price paid. Thus, we look for a PBE in which informed bidders always bid q.

Knowing this, when we define the optimal bid for *uninformed* bidders, it must be a best response when all *informed* bidders bid q. Suppose for now that each of the other players becomes informed with probability ρ, and further suppose they bid q when informed and $b^\star$ when uninformed. The *ex post* price paid by player i from bidding b_i then depends on whether she wins the auction and whether the second-highest bid, $\max b_{-i}$, was made by an informed or uninformed bidder:

Case I: $\max b_{-i}$ *is made by an informed player.*
Here i always pays q *ex post*, whether in the auction or the aftermarket. If $b_i < \max b_{-i}$ she loses the auction and pays q in the aftermarket. If $b_i > \max b_{-i} = q$, she wins the auction and pays q.

Case II: $\max b_{-i}$ *is made by an uninformed player.*
Here i will either pay q or $b^\star$ *ex post*, depending on whether she wins the auction. If she submits any bid $b_i' < b^\star$ she loses the auction and pays q in the aftermarket. If she submits any bid $b_i'' > b^\star$, she wins the auction and pays $b^\star$. If instead, she bids $b_i = b^\star$, the tie-breaking rule ensures that she sometimes wins and sometimes loses the auction, paying $b^\star$ if she wins and q in the aftermarket if she loses.

Since bidding $b < b^\star$ will guarantee that a player will only win when all other bidders are informed and $q < b$, such a bid will ensure an uninformed bidder will expect to pay $\mathbb{E}q$ for the good. To be willing to bid and thus sometimes win the auction at a price of $b^\star$, an uninformed bidder must expect to pay a price of no more than $\mathbb{E}q$ when placing a bid that could win against $b^\star$. *Ex ante* indifference between placing a bid that would win or lose to other uninformed bidders when they bid $b^\star$ provides the restriction for it to be the PBE bid of all uninformed players.

Thus to solve for $b^\star$, equate the expected price paid when bidding above $b^\star$ and the expected price when bidding below $b^\star$. This gives the restriction:

$$\mathbb{E}q = (1-\rho)^{n-1}b^\star + \rho^{n-1}\mathbb{E}q + (1-\rho^{n-1}-(1-\rho)^{n-1})\left[\int_{\underline{q}}^{\overline{q}} \max[b^\star, q]dG(q)\right].$$

Rearranging the above gives:

$$(1-\rho)^{n-1}\left[\mathbb{E}q - b^\star\right] = (1-(\rho)^{n-1}-(1-\rho)^{n-1})\left[\int_{\underline{q}}^{\overline{q}} \max[0, b^\star - q]dG(q)\right]. \qquad (1)$$

When $n = 2$, the right-hand side of (1) equals zero, and thus $b^\star = \mathbb{E}q$. But when $n > 2$, (1) implicitly defines the uninformed bid $b^\star$ given ρ, the probability of becoming informed.[12] Since the implied $b^\star$ exceeds $\underline{q}$, it follows that uninformed players will sometimes overbid (and sometimes underbid) the aftermarket price. The bidding strategy of an uninformed player thus generates behavior consistent with the "bidder's curse". It remains to be shown that some bidders will choose to be uninformed in equilibrium.

[12]See Lemma 1 in Appendix A for the full argument. Notice that when $n > 2$, the right-hand side of (1) will be positive, and will generally be strictly positive – implying that $b^\star < \mathbb{E}q$. In a symmetric equilibrium with more than two bidders, a given uninformed bidder would only win the auction against a mix of both uninformed and informed opponents by paying strictly above the aftermarket price. To avoid a winner's curse, an uninformed bidder must expect to pay strictly less than the aftermarket price in the case where all other bidders are also uninformed – which requires that the uninformed bid be less than $\mathbb{E}q$.

2.3 Information acquisition

Given what we have shown so far about bidding strategies, we can now consider the costs and benefits of becoming informed before bidding in the auction. Information acquisition is costly because player i must forgo c_i to become informed. Acquiring information is beneficial because it eliminates the possibility of overpaying relative to the aftermarket price and raises the likelihood of getting a bargain in the auction against uninformed bidders whenever $b^\star < q$. We characterize the PBE information acquisition strategy in which a player becomes informed whenever these expected benefits exceed the costs, given the expected information acquisition strategies of others.

Let ι represent the information acquisition strategy of $-i$. If i has rational expectations about others' behavior, then i's *ex ante* assessment of the probability of each other player becoming informed, ρ, is given by:

$$\rho = \int \iota(c) dF(c) \tag{2}$$

Using the bidding strategies of $-i$ derived above, an informed bidder pays a price q either in the auction or the aftermarket whenever at least one other bidder is informed, but pays the minimum of q and $b^\star$ when no other player is informed. Thus the expected price paid, conditional on choosing to lookup the aftermarket price, is given by

$$(1-\rho)^{n-1} \int \min[q, b^\star] dG(q) + \rho^{n-1}\mathbb{E}q + \left(1 - \rho^{n-1} - (1-\rho)^{n-1}\right)\mathbb{E}q.$$

As noted earlier, in equilibrium, uninformed bidders pay an expected price of $\mathbb{E}q$. The expected savings from acquiring information is then given by

$$(1-\rho)^{n-1} \int \max[0, q - b^\star] dG(q) \tag{3}$$

Notice that, conditional on $b^\star$, the value of becoming informed is declining in ρ; that is, players' information acquisition decisions are strategic substitutes. This is because when other players are likely to be informed, it is more likely that all other bids in the auction will equal the aftermarket price, which eliminates the benefit of being informed. In contrast, when no other bidder is informed, then a given bidder who looks up the price can save $b^\star - q$ whenever $q < b^\star$, though the probability of getting these savings decreases as ρ increases.

In equilibrium, each player acquires information when the value of information, (3), is greater than c_i and remains uninformed whenever it is less than c_i. Thus i follows ι if it is consistent with the cutoff strategy:

$$\bar{c} = (1-\rho)^{n-1} \int \max[0, q - b^\star] dG(q) \tag{4}$$

$$\iota(c) = 0 \text{ if } c > \bar{c} \tag{5}$$

$$\iota(c) = 1 \text{ if } c < \bar{c} \tag{6}$$

These equations together with (2) fully characterize an ι consistent with symmetric PBE, given $b^\star$.[13] Thus agents weigh the benefits of avoiding overpaying (and potentially underpaying), relative to q, against their opportunity costs, and some will find it rational to remain ignorant.

If $\rho = 1$, then an uninformed bidder pays an expected price of $\mathbb{E}q$ (regardless of her bid in the auction), as does an informed bidder. But then if $c_i > 0$, a player is strictly better off by remaining uninformed. Thus so long as $F(0) < 1$, some bidders will choose to remain uninformed in equilibrium. Since opportunity costs are rarely zero, our theory predicts that rationally ignorant agents will be present in both lab and field markets and will influence auction prices.[14]

2.4 Equilibrium

The equilibrium described is summarized in Proposition 1 below.

Proposition 1. *Existence of Symmetric PBE*

The game described above has a symmetric PBE which can be described by an information acquisition function ι and an uninformed bid $b^\star$ that satisfy (1)-(6) such that each player follows the strategy given by (A)-(D).

[13] Note that if F has mass points, (4) - (6) also pin down the probability of acquiring information at $\bar{c}$, $\iota(\bar{c}) \in [0,1]$, when necessary. The right-hand side of (4) is weakly positive, strictly decreasing in ρ, and takes all values between 0 and $\int \max[0, q - b^\star] dG(q) \geq 0$. To find the cutoff value $\bar{c}$, substitute in $\rho = F(\bar{c})$ into the right-hand side, and starting at $\bar{c} = 0$, increase $\bar{c}$ on the right-hand side of the equation until the first point at which the right-hand side is weakly less than the left-hand side. This point is the desired $\bar{c}$. If the right-hand side is strictly below $\bar{c}$ at this point, we can find a $\rho \in [\lim_{c \uparrow \bar{c}} F(c), F(\bar{c})]$ to make the desired equality hold, pinning down $\iota(\bar{c})$.

[14] If $\rho = 0$, then by (1), uninformed agents would bid $\mathbb{E}q$. Then by (3) they would find it worthwhile to become informed if $\int \max[0, q - \mathbb{E}q] dG(q) > c_i$. Thus so long as $F(\int \max[0, q - \mathbb{E}q] dG(q)) > 0$, some bidders will choose to become informed in equilibrium.

In this equilibrium, if $F(0) < 1$ *then* $\rho < 1$*, and if* $F(\int \max[0, q - \mathbb{E}q]dG(q)) > 0$ *then* $\rho > 0$.

Uniqueness of the Symmetric PBE In Appendix A, we show that in every symmetric PBE, types who become informed bid the aftermarket price, q, with a probability of 1; types who remain uninformed pay an expected price of $\mathbb{E}q$. Thus, information acquisition decisions are given by a cutoff strategy in c_i consistent with (4)-(6).

Below we describe an experiment that allows us to test the behavioral implications of symmetric PBE, in particular on overbidding (relative to q) and rational ignorance.

3 Experimental Design, Procedures, and Predictions

The experiment consists of two parts, the "Productivity Measurement" part and the "Market" part. In the "Productivity Measurement" part, each subject participates in three, two-minute periods of a real-effort 'slider task' due to Gill and Prowse (2012) with a break of one minute in between periods. Subjects observe a screen with 48 sliders, each representing a scale from 0 to 100 (See Figure B5 in Appendix B below). The sliders are initially set to "0", and subjects receive a payment $k^* = 1$ Experimental Currency Units (ECU) for each slider that they set to "50" by the end of the two minutes. Observing behavior in this part allows us to control for individual skill heterogeneity when attempting to understand the role of opportunity cost in influencing bidding behavior.

After the Productivity Measurement part, subjects participate in the Market part, consisting of a sequence of $T = 16$ unrelated markets in which they attempt to buy a single unit of a fictitious item. In each market, one unit of supply is available in an ascending auction, and – after the auction ends – unlimited supply is available at a fixed price for those who did not obtain the unit in the auction and still wish to purchase it. At the beginning of each market, subjects observe their induced value for the item v and their slider task payment rate k (which are each drawn independently for each subject), and are reminded of the distribution from which the fixed price is drawn. Importantly, if they want to learn the actual fixed price before bidding in the auction, they must choose to forgo the opportunity to earn additional income in another 30 seconds of the slider task, where they receive k ECU per correctly placed slider. Hence, by varying the value of k in the slider task, we vary the opportunity cost c_i of looking up the fixed price, and we can observe the effect of opportunity cost on the probability of overbidding in the auction. Recent evidence suggests that effort in the slider task is not very sensitive to changes in the piece rate (Araujo et al., 2016). This means that expected payoffs are directly proportional to k, such that our method of inducing opportunity cost is not likely to be affected by different degrees of effort, conditional on participation in the slider task, for different values of k.[15]

Next, those subjects who choose not to look up the fixed price participate in 30 seconds of the slider task in which each correctly placed slider yields a return of k, while those who choose to forgo the slider task can observe the fixed price displayed on their screens for 30 seconds. At the end of the 30 seconds, subjects submit their bids in the clock auction with the highest bidder winning the auction and paying the second-highest bid. To ensure that we observe the high bid, bidders did not observe the dropping behavior of their competitors and the auction clock stopped when the last bidder dropped from the auction. Then, each subject learns whether they were able to purchase the good at auction and the auction price, and those subjects who were unsuccessful are then given the opportunity to purchase the item at the fixed price. Just before the decision to purchase is made, the fixed price is revealed to all remaining buyers at no cost, and subjects simply choose whether or not to buy at the revealed price. This concludes the first market. At the end of the first market, the second market begins, and so on until all 16 markets have closed.

Each market consists of $n = 2$ bidders chosen from a matching group of size $N = 8$. For each market, each subject receives a randomly drawn integer value denominated in ECUs, $v \sim U[50, 100]$, and we draw the fixed price, $q \sim U[0, 50]$, to ensure that the possibility of overbidding (almost) always exists. Over the sequence of 16 markets, the value of k in the slider task varies randomly. Specifically, k is drawn independently for each bidder from the set $\{0, 0.25, 3, 6\}$ with equal probability of each value, and subjects are clearly informed of this.[16] We randomly rematch within groups so that each bidder faces each value of k four times, on average. Hence, we are able to capture the benefits of both a between and within subjects comparison of the treatment effect.

Subjects are rematched across markets and receive no additional information about

[15] Indeed, our data provide additional support for the claim made by Araujo et al. (2016); if we regress observed effort on k, conditional on participation in the slider task, we find no significant relationship. This suggests that the disutility of effort in our task is roughly constant across k and so we ignore it in our analysis.

[16] We also ran two unreported pilot sessions with $k \in \{0, 0.25, 1, 5\}$. We obtained qualitatively similar results but less overbidding of the fixed price with these parameter values, which is consistent with our predictions.

the other bidders in their market. The bidder's role in each market is framed as that of an agent who can buy a commodity for resale to the experimenters at a pre-agreed price $= v$. In the auction stage of the market, the clock starts at 0, and increases in unit increments until a price of 105 ECU. At any time, each bidder can press a button labeled "Stop Bidding" to drop out of the auction; their bid is given by the price at which they stop bidding. Once both bidders have dropped out, each bidder is informed whether they won the auction and the price at which the earliest bidder dropped out, which gives the price paid by the winning bidder (as in a second-price auction).

We employ an ascending auction because this has been shown to facilitate comprehension and reduce overbidding relative to sealed-bid alternatives (Kagel et al., 1987). Eliciting drop-out prices from all bidders represents a deviation from the typical clock auction, but it allows us to observe the entire distribution of bids, so that we can test the full set of predictions from our theory.[17] See Appendix B below for screenshots and a complete set of instructions, which were provided to subjects on paper and read aloud by the experimenter.

At the end of the experiment, we randomly select one market for each subject for payment. ECUs are converted to Canadian dollars at a rate of 10 ECU = \$1. Then subjects receive private cash payments including a \$7 payment for arriving to the experiment on time, their earnings from the Productivity Measurement stage, and their earnings from the randomly selected market (including what they earned in the slider task, if they participated). Prior to beginning the incentivized markets, subjects participated in two practice markets that were unpaid to familiarize themselves with the institution.

In total we ran 8 sessions of 8 subjects drawn from the undergraduate population of a mid-sized North American university (average age = 22, 38% Male). Our online recruitment system includes students from all disciplines. We emailed a random subset of eligible students invitations to participate in our experiment. The only restriction on participation was that the subjects could not have any prior experience in this experiment. On average, subjects earned \$19 for a 90-minute session, including show-up payment.

3.1 Predictions

The model introduced in section 2 shows how the opportunity cost of researching the aftermarket price leads to behavior that looks like the bidder's curse. Here, we detail the

[17] See also Engelmann and Wolfstetter (2009) who provide evidence that the standard clock auction conceals overbidding due to selection bias. As we show below, this is consistent with our observations.

behavioral implications of the symmetric PBE of our rational model for our experiment where $n = 2$. In our model, all informed bidders bid q and therefore never overbid the aftermarket price. Uninformed bidders, however, always bid $\mathbb{E}q$, and when $\mathbb{E}q > q$, they will overbid the aftermarket price (which occurs almost half of the time in equilibrium.) The presence of uninformed bidders is entirely driven by the opportunity cost of looking up the aftermarket price. When the cost of acquiring this information is sufficiently high, bidders find it in their interest to remain uninformed, and as a result, they may overbid the aftermarket price. We state five testable predictions of our model below:

1. Information Acquisition. Each player follows a cutoff information acquisition strategy: there exists a cutoff $\bar{c}_i$ such that the player looks up the price whenever $c_i < \bar{c}_i$ and does not look it up whenever $c_i > \bar{c}_i$. Subjects are more likely to remain uninformed at higher values of c_i.

2. Overbidding. Uninformed bidders will sometimes overbid the aftermarket price, but informed bidders will not. Allowing for errors or other sources of overbidding, the relative frequency of overbidding will be higher for uninformed than for informed bidders.

3. The Bidder's Curse. Since uninformed bidders will sometimes overbid, they will also sometimes overpay relative to the fixed price (the bidder's curse). Overpayment is most likely when both bidders remain uninformed.

4. Rationality of Ignorance. Uninformed bidders achieve higher payoffs, on average, than they would have by acquiring information, even when their bid exceeds the aftermarket price.

5. Bidding Strategies. Informed bidders bid q. Uninformed bidders bid $\mathbb{E}q$ and are, hence, equally likely to over- and under-bid the aftermarket price.

We now use our experimental data to test both the comparative statics and the point predictions of our model.

4 Experimental Results

In the following section, we detail the main experimental findings. In preview, we see 1) that subjects largely acquire information in a rationalizable way, 2) that uninformed bidders are prone to overbid, relative to the aftermarket price, 3) that the presence of uninformed overbidders in an auction regularly generates a bidder's curse, and 4) that such behavior reflects rational ignorance, since the payoffs subjects receive when they remain uninformed and overpay exceed the counterfactual payoffs they would have received had they instead become informed. We present the results in the order noted above to emphasize the mechanism by which the bidder's curse is generated. It also simplifies the exposition because the presentation parallels the model. We then conclude our results with a thorough analysis of individual bidding behavior.

4.1 Information Acquisition

Figure 1a shows a histogram of the number of correctly completed sliders by each subject in the incentivized portion of the productivity measurement part of the experiment. On average, subjects completed 18.9 sliders in the available two minutes, but the data reveal substantial heterogeneity in performance (std. dev. = 8.2, and range: 1-48).

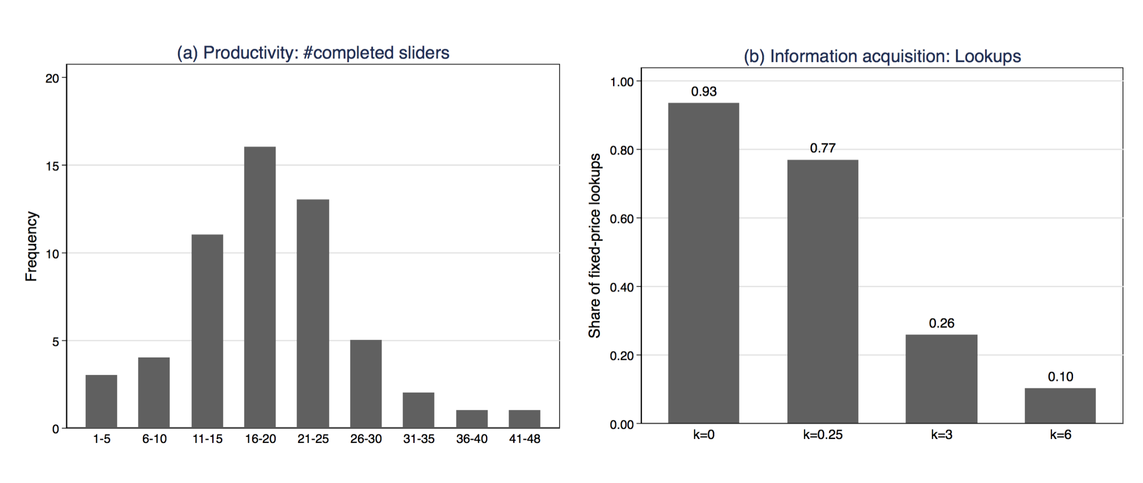

FIGURE 1: Productivity measurement and information acquisition

Our market stage data consist of 1024 price lookup and bidding decisions from 512 markets. Overall, we observe 510 instances (50%) in which bidders look up the aftermarket price. Under the theory, individuals acquire information only when doing so is worthwhile. In particular, theory predicts that individuals follow a cutoff strategy, acquiring information whenever their opportunity cost is sufficiently low – that is, whenever $k_{i,t}$ is below a subject-specific threshold that depends in the experiment on a subject's productivity in the slider task. We test whether subjects play cutoff strategies using lookup decisions for each subject at each level of k. We find that 50 out of 64 subjects (78%) use a cutoff strategy; that is, their choices are consistent with the existence of some cutoff value $\bar{k}_i$ such that subject i always looks up the aftermarket price when $k_{i,t} < \bar{k}_i$, but never looks it up when $k_{i,t} > \bar{k}_i$.

While adherence to cutoff strategies is observed for a large majority of subjects, a weaker implication of the theory is that the overall likelihood of remaining uninformed is increasing in the opportunity cost of acquiring information about the aftermarket price. This is what we see in the data on average. When the opportunity cost k is 0, subjects lookup the aftermarket price 93% of the time (see Figure 1b).[18] This share steadily declines in k, with subjects choosing to lookup the aftermarket price 77% of the time when k is 0.25, 26% of the time when k is 3, and only 10% of the time when k is 6. A probit regression analysis with standard errors clustered at the session level provides statistical support, indicating that the probability of looking up the fixed price is decreasing in k (p-value < 0.001), controlling for a bidder's value v and for the market period. See Table C1 in Appendix C for complete estimates.

To better account for the impact of heterogeneity in individual slider task performance, we analyze information acquisition more closely. Recall that a rational bidder compares the benefits of the slider task to the benefits of becoming informed about the fixed price. Whenever slider benefits exceed the benefits of becoming informed, the bidder prefers to remain ignorant of the fixed price, and vice versa. At the cutoff value, slider benefits are equal to lookup benefits, so that the bidder is indifferent. With our experimental parametrization, the cutoff value under risk-neutrality is given by:[19,20]

$$\bar{c} = (1 - \rho) \cdot 6.25 \text{ ECU}$$

which decreases in ρ, the probability that a bidder becomes informed.

We can put bounds on the rationalizable values of ρ, which then implies a set of rationalizable cutoff values $\bar{c} \in [1.57, 4.69]$ ECU.[21] This means (i) that all rational subjects

[18]In theory, they should look it up 100% of the time, so this deviation is itself a bit puzzling. We are reluctant to speculate on the reason, but as we emphasize below, despite the deviations in terms of point predictions, the comparative statics are quite consistent with the theory.

[19]The equilibrium cutoff value is given by (4). For $n = 2$ bidders, uniformly distributed aftermarket prices between 0 ECU and 50 ECU, and $b^\star = 25$, this reduces to: $\bar{c} = (1-\rho)\int_{25}^{50} \frac{1}{50}(q-25)dq$, which can be solved for $\bar{c} = (1-\rho)\frac{1}{50}\left[(0.5\cdot 50^2 - 25\cdot 50) - (0.5\cdot 25^2 - 25\cdot 25)\right] = (1-\rho)\cdot 6.25$.

[20]For clarity of exposition, we assume risk-neutrality in what follows, but note that allowing for heterogeneous risk preferences would expand the set of rationalizable cutoffs.

[21]Since each subject's opponent has a 0.25 chance of facing $k = 0$ ECU and thus having zero benefit of doing the slider task, we can bound $\rho \geq 0.25$ and thus $\bar{c} \leq 4.69$. Then, any subject who can complete

should become informed about the fixed price when $k = 0$ and (if they can complete at least one slider) remain uninformed when $k = 6$ and (ii) depending on individual slider task proficiency, information acquisition decisions can rationally differ across subjects for $k = 0.25$ and $k = 3$. Specifically, when $k = 0.25$, only highly productive subjects who expect to complete at least 7 sliders can earn more in the slider task than the lowest rationalizable cutoff value, and so the majority of subjects should look up the fixed price. When $k = 3$, the majority of our subjects, who can expect to complete two or more sliders, can earn more than the highest rationalizable cutoff value and should remain uninformed.

Observed behavior is consistent with these predictions, on average, as shown in the right panel of Figure 1. However, we can further assess whether *individual* information acquisition is rationalizable more carefully, by comparing (expected and actual) slider task benefits to expected lookup benefits for each decision. To do so, when a subject did not look up the fixed price we use their actual slider task earnings; when they did look up the fixed price, we impute their slider task earnings using their most recent slider task performance and the k value they faced.

Figure 2 shows the CDFs of actual slider benefits when forgoing information acquisition and forecasted slider benefits when acquiring information. As can be seen, 86% of the lookup decisions and 89% of the no-lookup decisions are rationalizable by this method, and a probit regression analysis shows that this frequency does not vary significantly with experience (full details in the Appendix). Note, however, that this approach assumes equilibrium bidding when computing the value of information acquisition; to account for deviations from equilibrium bidding, in Section 4.4 we conduct additional analyses to test whether subjects who remained uninformed indeed earned more than they could have by learning the fixed price, given the actual auction bids of their counterparts.

Finding 1: Subjects generally acquire information about the aftermarket price in a manner consistent with a cutoff strategy. Moreover, the probability of looking up the aftermarket price is decreasing in the opportunity cost.

Note that a cutoff strategy in which a bidder sometimes remains uninformed can lead to overbidding relative to the fixed price, so that the bidder's curse occurs. Specifically, an uninformed bidder will overbid the fixed price in equilibrium almost half the time; i.e. when the actual fixed price is less than the expected fixed price. We next examine the

at least one slider (which we observed in 506 out of 514 instances, 98.4%) will always wish to complete the slider task when $k = 6$. Thus, $\rho \leq 0.75$, so that the lower bound of rationalizable cutoffs is $\bar{c} \geq 1.57$.

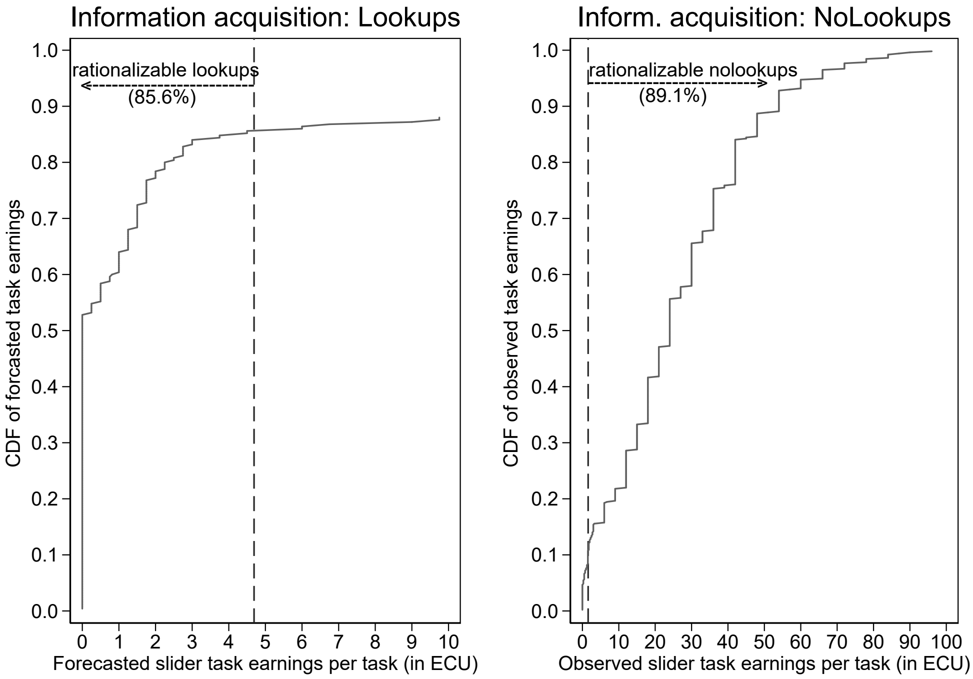

FIGURE 2: Rationalizable information acquisition

impact of information acquisition on bidding behavior.

4.2 Information and Overbidding

Overall we see 463 instances of overbidding the aftermarket price – 45% of all bids. Summary statistics reported in Table 1 shows both the conditional and unconditional fraction of subjects to lookup the fixed price and overbid for each possible opportunity cost k. When subjects choose not to look up the fixed price, they overbid 57% of the time. Subjects are less likely to overbid when they choose to become informed; in this case they overbid only 33% of the time. A probit regression analysis with standard errors clustered at the session level provides statistical support, indicating that the probability of overbidding the fixed price is significantly lower when a bidder has looked up the fixed price (p-value < 0.001), controlling for a bidder's value v and for the market period; full regression results are in Table C3 of Appendix C.[22] While the data are consistent with the comparative statics of the model, we see more overbidding than predicted, both among

[22]Since the decision to overbid is a function of the endogenous decision to become informed, we also estimate a bivariate probit model that accounts for the endogeneity of the information acquisition decision when estimating the impact on the likelihood of overbidding. See Table C5 and the accompanying discussion in Appendix C.2. These estimates provide qualitatively the same interpretation as that provided by the analysis reported in the main text, so we have chosen to report the simpler model here.

the informed and the uninformed. We return to this issue in more detail below when we analyze bidding strategies in Section 4.5.

k	$Pr(Lookup)$	$Pr(Overbid\|Lookup)$	$Pr(Overbid\|NoLookup)$	$Pr(Overbid)$
0	.93	.35	.59	.37
0.25	.77	.26	.60	.34
3	.26	.36	.54	.49
6	.10	.54	.59	.59
Total	.50	.33	.57	.45
N	1024	510	514	1024

TABLE 1: Summary statistics on the probability of overbidding, conditional on k.

Finding 2: Overbidding relative to the aftermarket price is more common among those who choose to remain uninformed.

A disadvantage of following the cutoff strategy and sometimes overbidding is that it can lead to the bidder's curse, where the auction winner pays a price exceeding the aftermarket price. In equilibrium, this can occur if both bidders remain uninformed, and so we next examine how the likelihood of the bidder's curse relates to the decision to become informed.

4.3 The Bidder's Curse

Overall, 23% of the auctions ended up with prices greater than the aftermarket price.[23] This ranges from 37% when neither bidder is informed, to 7% when both bidders are informed (see Figure 3). Another probit regression analysis with standard errors clustered at the session level provides statistical support, indicating that the probability of an auction winner falling prey to the bidder's curse (i.e. the auction price exceeding the fixed price) is significantly lower when either one or two bidders have looked up the fixed price (p-values $= 0.076$ and < 0.001 for one and two informed bidders, respectively), controlling for the winning bidder's value v and for the market period (see Table C4 Appendix C for full regression results). Again, though the data are consistent with the comparative statics of the theory, we observe the bidder's curse more often than expected when either 0 or 1 bidder is informed and *less* often than expected when two bidders are

[23]Recall that we conducted auctions with two bidders. With more than two bidders, the probability of overpaying may increase.

uninformed. We return to this fact below when discussing individual bidding behavior in Section 4.5.

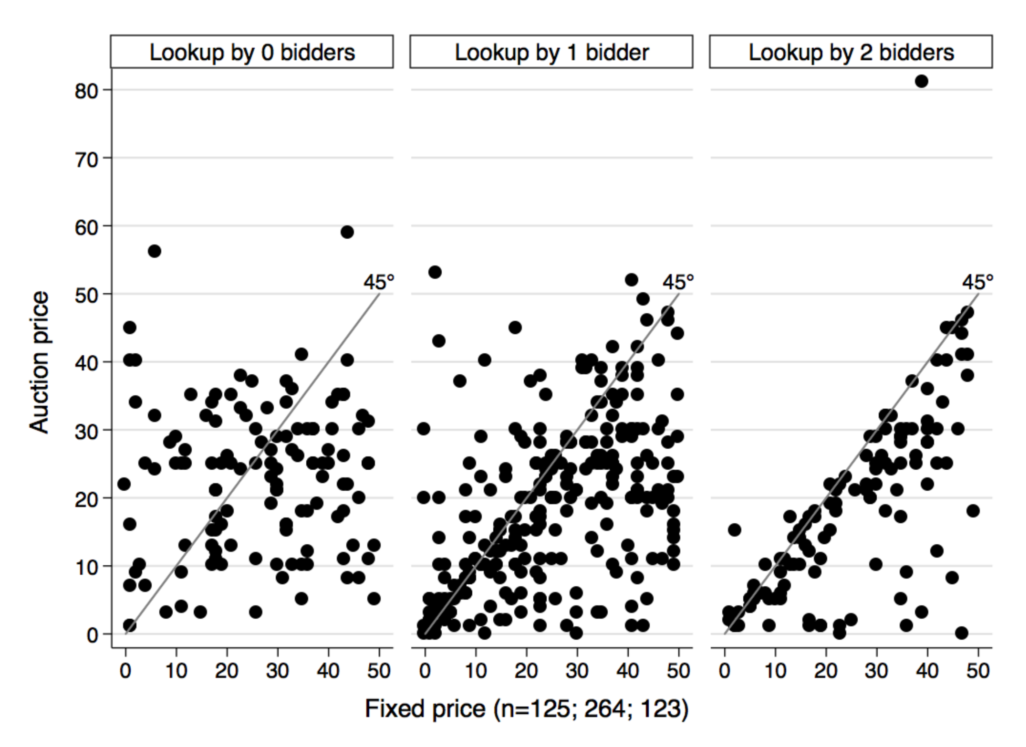

FIGURE 3: The relationship between auction prices and fixed prices when 0, 1 and 2 bidders chose to look up the fixed price

Finding 3: The bidder's curse occurs most often when both bidders remain uninformed about the aftermarket price, though it still arises occasionally when one or both bidders are informed.

Note that, under the theory, it is individually rational to sometimes fall prey to the bidder's curse, because avoiding it in any circumstance is too costly. Thus we next analyze whether subjects who fell prey to the bidder's curse nevertheless earned more than they would have by becoming informed about the aftermarket price and bidding accordingly.

4.4 The Rationality of Ignorance

To see the empirical earnings impact of remaining uninformed, we estimate a linear panel regression, with heteroskedasticity-robust standard errors and random effects for each subject to control for individual differences, where the dependent variable is the total net gain of an auction winner i in market t ($\pi_{i,t}$), relative to obtaining the good in the aftermarket. Let p_t represent the price paid by the winning bidder in the auction during market t (which is always less than or equal to the winning bid), and let q_t represent the fixed price at which the item can be purchased in the aftermarket. The winning bidder's earnings from the auction are then $q_t - p_t$. However, this is not the only component of earnings during a market since bidders may also participate in 30 seconds of the slider task to earn additional money. Let e_t^{II} be the number of sliders correctly adjusted in market t during part II; then total earnings from the slider task are $k_t e_t^{II}$, where k_t is the value of correctly adjusting a single slider.[24] Thus, we define total net gains in market t as $\pi_t = k_t e_t^{II} + (q_t - p_t)$. The independent variables of the regression include a constant term, a dummy variable that takes a value of 1 when the bidder was uninformed and 0 otherwise ($!\lambda_{i,t}$), and an interaction between the uninformed dummy variable and the slider task earnings ($k_t e_{i,t}^{II}$).

$$\pi_{i,t} = \gamma_0 + \gamma_1 !\lambda_{i,t} + \gamma_2 !\lambda_{i,t} k_t e_{i,t}^{II} + \eta_i + \epsilon_{i,t} \tag{7}$$

Table 2 reports the output of this regression. A positive and significant coefficient on the constant term indicates that informed bidders stand to gain approximately 9 ECU in the auction. Uninformed bidders sacrifice approximately 4 ECU because they tend to overbid the aftermarket price; however, we can reject the hypothesis that an uninformed bidder who earned nothing in the slider task would receive a total payoff of 0 (i.e. a Wald test that $\gamma_0 + \gamma_1 = 0$ yields $\chi^2 = 7.51$, p-value < 0.01). This is driven by the presence of people who submit below equilibrium bids, sometimes generating a deal for the auction winner (see section 4.5). Note that this is not a very risky strategy since such bidders will pay the aftermarket price when they lose in the auction. The coefficient on the interaction term (mechanically) equals 1, and evaluated at the mean of $k_t e_{i,t}^{II}$, which is 13, we can reject the null hypothesis that uninformed bidders and informed bidders receive the same mean payments in favor of the alternative that uninformed bidders' earnings are greater (a Wald test that $\gamma_1 + 13\gamma_2 = 0$, yields $\chi^2 = 26.62$, p-value < 0.01).

Finding 4A: On average, uninformed bidders earn more than they would have earned by becoming informed about the aftermarket price.

Moreover, as noted above, overbidding relative to an aftermarket price (as opposed to one's value) need not make the bidder worse off. If the opportunity cost of looking

[24]Note that here we use actual earnings from Part II rather than expected earnings, given performance in Part I.

	Total Net Gains ($\pi_{i,t}$)
No Lookup, $(!\lambda_{i,t})$	-4.35**
	(1.88)
Slider Task Earnings $(!\lambda_{i,t} \times k_t \times e^{II}_{i,t})$	0.97***
	(0.04)
Constant	8.84***
	(1.14)
R^2	0.62
N	512

Clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2: Panel linear regression explaining the total payoffs earned by auction winners.

up the fixed price is sufficiently high, the gains from bidding correctly in the auction may be outweighed by the forgone gains from alternative actions. To identify the impact of overbidding on earnings, we compute the total net gains ($\pi_{i,t}$) for the winner of each auction in which the winning *bid* was greater than the fixed price.

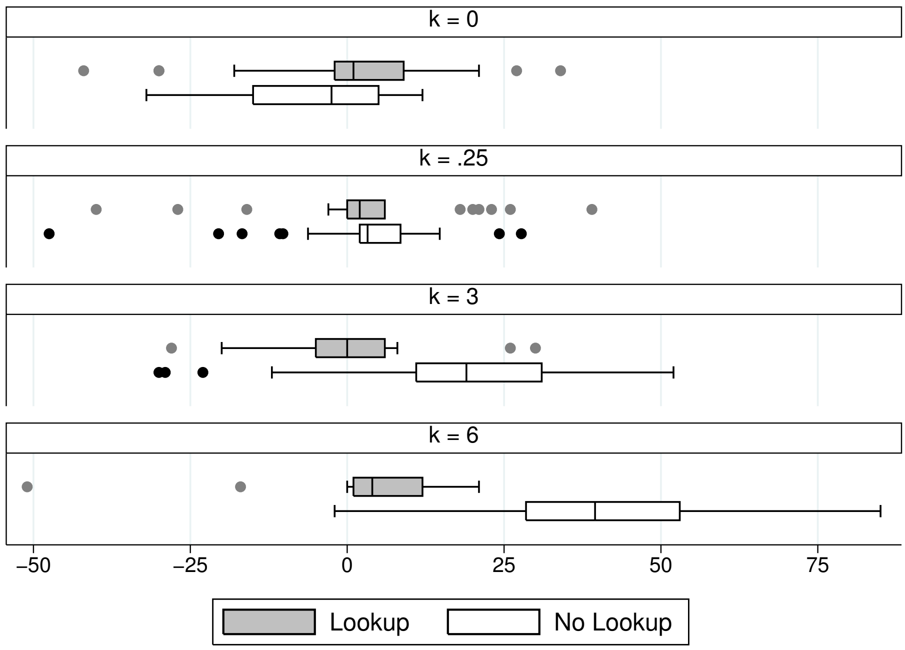

FIGURE 4: Box-and-whisker plots of total net gains (auction earnings + slider earnings) in ECU, for auction winners with $b_{i,t} > q_t$, conditional on the decision to lookup the fixed price.

Figure 4 displays box-and-whisker plots of total net gains ($\pi_{i,t}$) of auction winners who submitted bids greater than the fixed price for each level of opportunity cost k (i.e. those bidders subject to the bidder's curse). In general, overbidding the fixed price had a *positive* impact on monetary earnings after taking into account earnings from the slider task; auction bidders who did not lookup the aftermarket price, overbid, and then won the auction earned an average of 27 ECU. Table 3 decomposes these earnings and shows that they would have earned only 4 ECU on average had they instead become informed and bid the aftermarket price (q_t). Gains from the slider task swamp any losses from overbidding. Cf. Figure 5, which displays empirical cumulative distribution functions of observed differences between the auction price and the fixed price, conditional on whether the bidder chose to lookup the fixed price.

Finding 4B: Bidders subject to the bidder's curse (i.e. $b_{i,t} > q_t$) earn positive payoffs on average and earn more than they would have earned by becoming informed.

	Uninformed (Actual)	Informed (Counterfactual)
Net Auction Savings ($q_t - p_t$)	0.48	4.11
Slider Task Earnings	26.65	0
Total Payoff ($\pi_{i,t}$)	27.13	4.11

Table 3: Earnings among overbidders who win the auction.

4.5 Bidding Strategies

In addition to the general implication that the opportunity cost of acquiring information about the aftermarket price drives overbidding, the model makes specific testable predictions about subjects' bidding strategies, conditional on information acquisition. In equilibrium, informed subjects bid the aftermarket price, and uninformed subjects bid the expected aftermarket price, $\mathbb{E}q$, which may be greater or lower than the actual aftermarket price. With our parameters, on average, they neither overbid nor underbid the aftermarket price. We test these implications of the model with the data.

On average, when informed, subjects bid 27 (median 25), and when uninformed they bid 32 (median 30). Among the overbids, 294 (63%) are made by uninformed bidders, and of the 344 sizable overbids ($b_{i,t} - q_t > 5$), the number made by uninformed bidders is

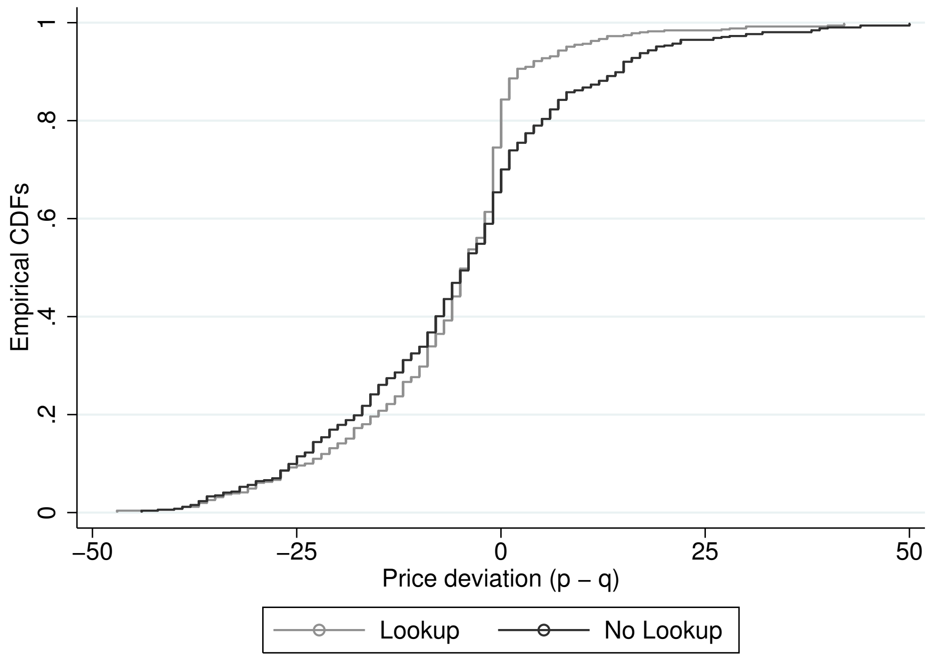

FIGURE 5: CDFs of net auction savings ($p_t - q_t$) for auction winners conditional on the decision to lookup the fixed price and the value of k

244 (71%). Figure 6 displays the relationship between bids and fixed prices conditional on the decision to lookup the aftermarket price for each value of k. The figure also displays equilibrium predictions and OLS fits to the data. As expected, bids often correspond to the fixed price when a bidder is informed, and we observe substantial overbidding, particularly when bidders are uninformed.

However, we also see evidence of substantial *under*-bidding relative to the theory, especially among uninformed bidders. This suggests that some subjects are deal-hunting, and this may help account for the aforementioned fact that we see the bidder's curse less frequently than expected when both bidders are uninformed and the fact that uninformed bidders earn positive auction profits on average.

To test the point predictions of the theory directly, we report GLS panel regressions where the dependent variable is the difference between the bid and the aftermarket price, and the independent variables include a constant term and a dummy that takes a value of 1 if the bidder chose to lookup the price and 0 otherwise. We include random effects for each subject to control for repeated measures and we cluster standard errors to control for heteroskedasticity. Column (1) of Table 4 reports the regression results. A positive and significant coefficient on the Constant term indicates that uninformed subjects overbid the aftermarket price by 6 ECU on average, so that bids are biased upward relative to the

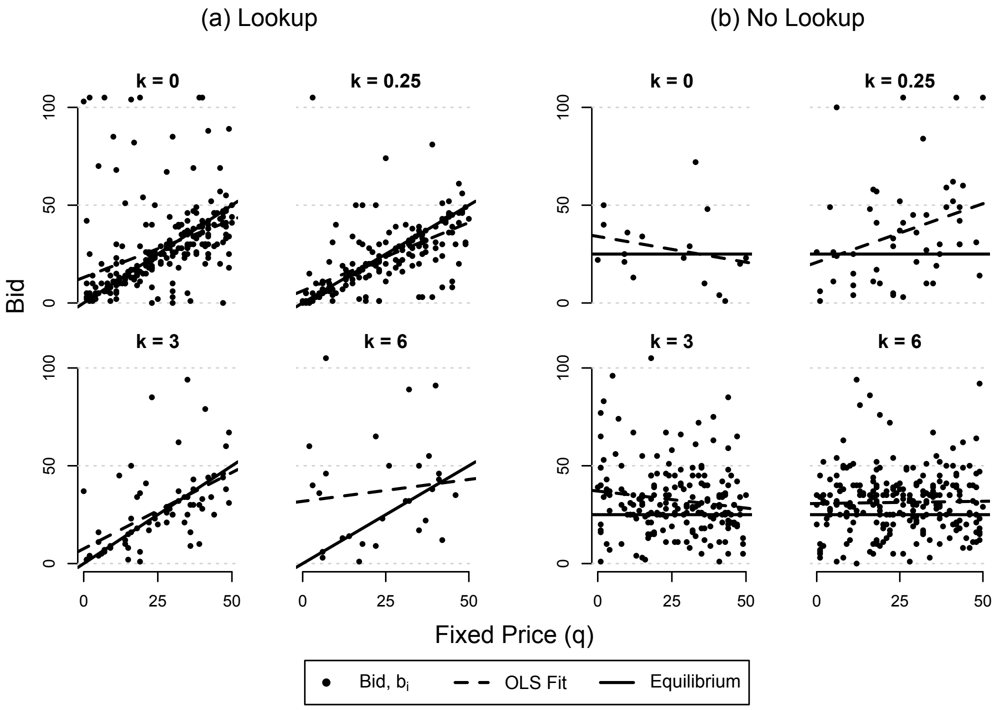

FIGURE 6: The relationship between bids and fixed prices by opportunity cost level and the decision to lookup the fixed price

theory. In contrast, bids made by informed bidders seem to be unbiased: The negative and significant coefficient on the Lookup dummy indicates that informed bidders reduce their bids significantly, and a Wald test cannot reject the null hypothesis that the Constant term and the Lookup term sum to 0, meaning that the overbidding amount among informed subjects is not significantly different from 0 on average.

The second regression in Table 4 allows us to compare observed behavior directly to the bidding strategies predicted by the theory. We report GLS panel regressions in which the dependent variable is the bid, and the independent variables include a constant term, a dummy that takes a value of 1 if the bidder chose to lookup the price and 0 otherwise, and an interaction between the aftermarket price and the lookup dummy, which allows us to test the extent to which informed subjects' bids reflect the aftermarket price. We include random effects for each subject to control for repeated measures, and we cluster standard errors to control for heteroskedasticity.

Column (2) of Table 4 displays the regression output. Informed bidders should bid exactly the aftermarket price, which implies that the coefficient on the Lookup × Aftermarket Price interaction will equal 1 and that the sum of the coefficients on the Constant term and the Lookup dummy will equal to 0. Uninformed bidders, on the other hand,

	Bid - Aftermarket Price $b_{i,t} - q_t$	Bid $b_{i,t}$
Lookup, $(\lambda_{i,t})$	-4.766***	-20.782***
	(1.735)	(2.299)
Lookup × *Aftermarket Price*		0.597***
		(0.066)
Constant	6.375***	32.398***
	(1.817)	(1.604)
R^2	0.012	0.125
N	1024	1024

Clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 4: GLS regression analysis of bidding behavior.

should bid $\mathbb{E}q$, which implies that the coefficient on the Constant term will equal 25 ECU, given our distribution of aftermarket prices. The regression coefficients reveal that uninformed bidders overbid substantially, and although informed subjects' bids respond significantly to the aftermarket price, and the lookup dummy is substantially negative, we still observe a tendency to overbid the aftermarket price on average. A Wald test rejects the joint hypothesis that all of the predictions are true ($\chi^2 = 22.81$, p-value < 0.01). We summarize the regression results as follows.

Finding 5A: Subjects on average tend to overbid relative to the theoretical predictions whether they inform themselves about the aftermarket price or not, although upward bias is pronounced only among uninformed bidders.

In addition to being slightly too high on average, bids in the experiment are also more diffuse than the equilibrium (point) predicts, especially among uninformed bidders (see Figure 7). For informed subjects, 13% of all bids are exactly equal to the aftermarket price, while 31% are within 1 ECU of the aftermarket price. Nearly half of all informed bids are within 5 ECU of the aftermarket price and 70% of all such bids are within 10 ECU. Uninformed subjects also do not bid exactly as predicted by the theory. In fact, only 7% of uninformed bids are exactly equal to $\mathbb{E}q$, i.e. 25 ECU, while only 12% are within 1 ECU and 51% within 10 ECU.

Finding 5B: Bids are more diffuse than predicted by the theory, particularly when subjects are uninformed.

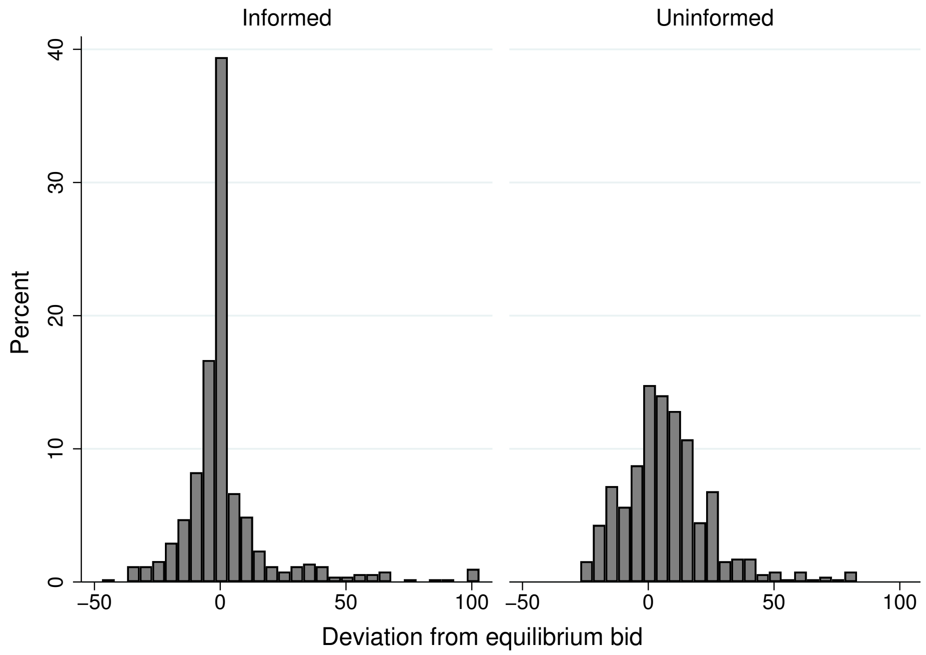

FIGURE 7: Histograms of deviations from equilibrium bidding ($b^* - b_{i,t}$). Note: *for uninformed bidders the maximum deviation below the equilibrium bid of 25 is -25 since negative bids are not possible.*

4.6 Behavioral Explanations of Bidding

Overbidding and excess bid dispersion by uninformed subjects remains a puzzle. One candidate explanation comes from the Malmendier and Lee (2011) notion of limited attention. We note that our data are inconsistent with bidders having limited attention in the sense described in their Proposition 3. If subjects simply ignore the aftermarket fixed price option, then it is optimal for them to bid $b_i = v_i$ as in Vickrey (1961). Only 4 out of 1024 bids are equal to v_i and 9% of bids are greater than 50 (the minimum of v_i), so this cannot explain our data.

Another possibility is that Finding 5A may be related to existing evidence of *on average* overbidding in second price auctions without an aftermarket (Kagel and Levin, 1993; Ariely et al., 2005; Cooper and Fang, 2008; Georganas et al., 2017).[25] We observe no consistent trends in the likelihood of overbidding across auctions; for example, informed (uninformed) subjects overbid with probability 0.36 (0.58) in the first five auctions and probability 0.32 (0.55) in the final five auctions. This is consistent with prior evidence, in

[25]Unlike a standard clock auction that ends when only one bidder remains, our auction does not have a solution in obviously-dominant strategies in the sense of Li (2017). Li suggests this might explain why past studies have tended to find less overbidding in ascending clock auctions than in otherwise equivalent second-price sealed-bid auctions. Our finding of overbidding lends support to his claim.

which even substantial experience does not eliminate overbidding (Kagel and Levin, 1993); however, we cannot rule out the possibility that additional experience would eventually eliminate overbidding.

Nevertheless, our data cannot be explained by many leading models that have been used to account for overbidding. For instance, introducing an additively-separable utility of winning would counterfactually predict a similar degree of overbidding by both informed and uninformed bidders (Cox et al., 1988). Similarly, introducing risk aversion as in the constant relative risk averse model in Cox et al. (1985) would lead to overbidding by uninformed bidders (since aftermarket price risk makes losing the auction less attractive) and could lead to a small amount of bid dispersion due to heterogeneity in values and in risk aversion, but would lead to neither for informed bidders since it remains weakly dominant for them to bid q.[26] Furthermore, while the level-k model has been successful in explaining overbidding in other settings (e.g. Crawford and Iriberri, 2007), it cannot explain overbidding in a second-price auction under the standard assumption that the level-0 type uniformly randomizes over bids, since informed bidders have a weakly dominant strategy to bid q and uninformed bidders of level-1 and higher would have a best response of bidding $\mathbb{E}q$.

One possible explanation relies on noisy behavior, as captured by quantal response equilibrium (Goeree et al., 2016). QRE assumes that each player behaves stochastically, but is more likely to choose actions that yield a higher expected value, given the stochastic behavior of other players. Thus the model can account for bid dispersion relative to the PBE. Moreover, in our setting QRE can generate more dispersion in bids by uninformed than by informed bidders (consistent with Finding 5B) and overbidding on average for both informed and uninformed bidders (consistent with Finding 5A).[27]

To see the intuition for higher dispersion among the uninformed, consider the incentives faced by agents when others play according to the PBE strategies given in section 2. Notice that an uninformed bidder will be indifferent across all bids. When combined

[26] For example, if we extend our model to allow bidders to be risk averse with a coefficient of relative risk aversion between .4 and .9 (consistent with the vast majority of subjects in the baseline and 20x treatments of Holt and Laury (2002)), the equilibrium uninformed bid increases, but only to 26 or 27. In theory, risk aversion could also lead more buyers to acquire information, since doing so reduces price risk. However, our theoretical simulations solving for equilibrium behavior with risk aversion show that this predicted effect is quantitatively negligible for our experimental setting.

[27] Another implication of QRE is that there is a positive probability that a subject will not buy in the aftermarket after losing in the auction, even though doing so is always payoff-maximizing. Surprisingly, this implication of QRE finds some qualitative support in the data. 12/64 subjects failed to purchase in the aftermarket after losing in the auction at least once. One subject did so 7 times, and in total there were 29 instances out of 512 in which auction losers failed to purchase in the aftermarket.

with QRE assumptions, the presence of this "flat maximum" generates dispersion in bids for the uninformed.[28] Also note that a given informed bidder strictly prefers to place a winning bid when the aftermarket price exceeds 25 and to place a losing bid when the aftermarket price is below 25. This intuition also extends to the QRE model where play is noisy, and players anticipate the noisy play of others. Under QRE informed bidders have incentives to bid close to q, while uninformed bidders have relatively weaker incentives to bid close to 25. Together these forces will tend to generate more dispersion in the bids of uninformed bidders relative to informed bidders.

To see the intuition for why QRE generates overbidding, note that the expected payoff consequences of deviations are roughly symmetric around the PBE bid. Since possible deviations are truncated below by 0 and above by 105 (the maximum clock price), there are more possible deviant overbids than underbids. As a result, noise in the QRE will tend to generate overbidding on average and at the median. Then, since uninformed bidders exhibit more dispersion, they will tend to overbid more in the model.

In Appendix C.3 we explore this intuition quantitatively by estimating a QRE model using our bidding data and describing how the estimated model can help explain some features, as well as some features of our data that the model gets wrong. This exercise gives a quantitative sense of the extent to which the intuition above can explain bid dispersion and overbidding which we summarize in Finding 6. We use our estimated model to predict the distributions of bidders' deviations from PBE predictions and display these in Figure 8.

Finding 6: A model of noisy behavior can plausibly account for both observed overbidding and excess dispersion.

5 Discussion

Our data suggest that overbidding a fixed price option becomes more likely as the opportunity cost of acquiring price information increases - consistent with the comparative statics of our model. We show that this drives much of the observed *ex post overbidding*, which is commonly called the bidder's curse. While the data are not perfectly consistent with the theory, they nevertheless support an interpretation in terms of rational ignorance.

While we were motivated by a particular pricing puzzle, our results suggest applica-

[28] The flat maximum problem is well-known in the context of second-price auctions (Harrison, 1989).

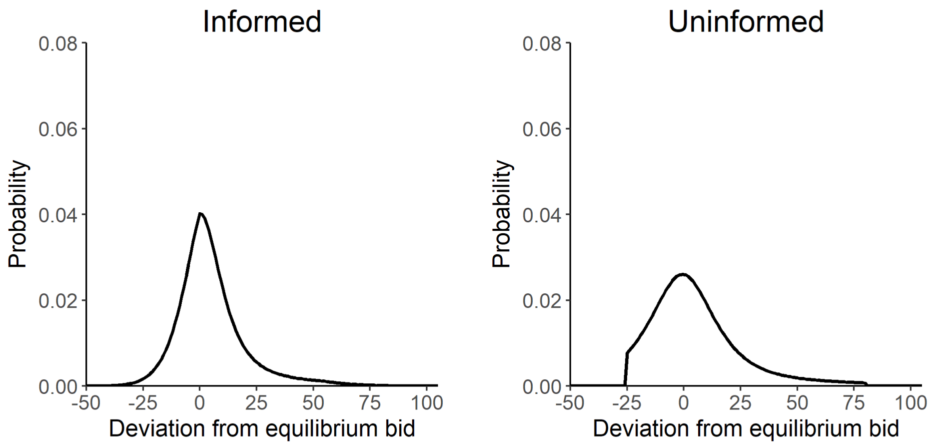

FIGURE 8: Estimated QRE-predicted densities of deviations from equilibrium bidding $(b^{*} - b_{i,t})$.

Note: *for uninformed bidders the maximum deviation below the equilibrium bid of 25 is -25 since negative bids are not possible.*

tions to the study of anomalies in markets more generally. One broader implication of this paper is that it can be important to account for opportunity costs of acquiring information in constructing a theoretical benchmark against which we might define behavior as anomalous. When opportunity cost is uncontrolled and unobservable, as in the field, behavior that appears consistent with the bidder's curse may instead reflect rational ignorance. For example, a similar mechanism can explain the phenomenon of jump bidding (Cramton, 1997; Avery, 1998) as an equilibrium response to the opportunity cost of repeatedly logging into an auction website to increase one's bid (Easley and Tenorio, 2004; Vadovič, 2017). Similarly, rational ignorance could account for "shipping-fee neglect" in online purchases (see e.g. Hossain and Morgan, 2006; Brown et al., 2010).

The presence of such tradeoffs is not unique to online purchases, and the sensitivity of many human decision-making processes to opportunity cost is well-known (Gigerenzer and Goldstein, 1996). In this sense, our results also complement previous findings that rationalize price dispersion via heterogeneous search costs, for example, the finding that unemployed people and retirees are more likely to buy items at a discount and use coupons (Narasimhan, 1984; Aguiar and Hurst, 2007; Kaplan and Menzio, 2015). In that setting as in ours, accounting for opportunity cost makes specific predictions about who will and won't "overpay", and if we ignore opportunity cost, higher prices paid by some buyers might be mistaken for a more general "buyer's curse".

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Appendix (for online publication)

A Theoretical Results

Lemma 1. *Given ρ, a there exists a value of $b^\star$ that solves the equation (1).*

Proof. The left-hand side of (1) is decreasing in $b^\star$ and the right-hand side increasing, both sides continuously since G has a continuous density. The right-hand side achieves a value of 0 at $b^\star = 0$ and $(1 - \rho^{n-1} - (1-\rho)^{n-1})(\bar{q} - \mathbb{E}q) > 0$ at $q = \bar{q}$. The left-hand side achieves a value of $(1-\rho)^{n-1}\mathbb{E}q > 0$ at $b^\star = 0$ and a value of $(1-\rho)^{n-1}[\mathbb{E}q - \bar{q}] < 0$ at $b^\star = \bar{q}$. □

By a standard argument, it is weakly dominant for an informed bidder to bid q. It remains to show that informed bidders bid q with probability 1 in any symmetric equilibrium.

Lemma 2. *In any symmetric PBE, informed bidders bid q with probability 1.*

Proof. Consider a candidate set of symmetric perfect Bayesian equilibrium strategies. Suppose that each player becomes informed with a strictly positive probability ex ante. Without loss of generality, a given player i can view other players' strategies as inducing a single (aggregate) mixed continuation bidding strategy over bids used by all informed players when q is the aftermarket price. Let σ denote the cumulative distribution function induced by this mixed strategy. Similarly, we can view the continuation strategies used when players choose to be uninformed as a inducing a single (aggregate) mixed continuation bidding strategy over bids used by all uninformed players.

For this set of candidate strategies to be supportable in a symmetric equilibrium, a player who is informed that the aftermarket price is q must be indifferent between any bids in the support of σ. The verbal argument below establishes that if σ puts a strictly positive probability on bids not equal to q, then bidding q achieves a strictly lower expected price than some bid in the support of σ.

So suppose that σ puts a strictly positive probability on bids strictly below q. Then if i bids q, the case where $-i$ all bid less than q occurs with strictly positive probability; in this case, i would pay the highest bid of $-i$, which is strictly less than q. But if i had instead made a bid $b < q$ in the support of σ for which $\sigma(q) > \sigma(b)$, i would pay the same price as if she had bid q when $-i$ all bid strictly below b. She must sometimes lose to bids equal to or exceeding b, in which case she would pay q in the aftermarket. If instead she had bid q, she would pay a price strictly below q. When $-i$ have at least one bid exceeding q, bidding q and bidding b will both lose and result in paying the same aftermarket price. Thus, bidding q must lead to a strictly lower interim expected price than bidding b in this case. It follows that σ cannot induce bids strictly below q with positive probability.

Similarly, if σ prescribes that bids strictly exceed q with strictly positive probability, we can apply the same logic to show that bidding q would always lead to a weakly lower price paid, and would with strictly positive probability lead to a strictly lower price paid than some bid exceeding q in the support of σ. Thus σ must prescribe bidding q with a probability of one. □

Lemma 3. *In any symmetric PBE, uninformed bidders pay an expected price of* $\mathbb{E}q$.

Proof. Consider candidate symmetric PBE strategies. Without loss of generality, view continuation strategies used conditional on remaining uninformed as inducing a single aggregate mixed continuation bidding strategy which generates a cumulative distribution function σ for uninformed types; let Q denote its support.

In a symmetric PBE, each uninformed player must be indifferent between bidding any point in the support of σ. If $\sigma(\bar{q}) < 1$, then any player i could achieve a higher ex ante payoff than any mixed strategy that prescribes bidding above $\overline{q}$ with positive probability by modifying the continuation strategy to change bids above $\bar{q}$ to $\overline{q}$ and this would contradict our assumption that σ forms part of a PBE. Thus $\sigma(\bar{q}) = 1$.

Let $\hat{b} = \sup\,[b :\ \sigma(b) = 0]$. If $\sigma(\hat{b}) = 0$, then there must a sequence b^n in Q with $b^n \to \hat{b}$. Since each $b^n \in Q$, each must yield the same expected price. Along this sequence, the equilibrium probability of winning the auction with a bid of b^n goes to zero; when a bid of b^n wins the auction, the ex post payment is bounded by $\max[b^n, q]$ while the payment is q when the bid of b^n loses the auction. Thus, as $b^n \to \hat{b}$, bidder i's expected payment for the good converges to $\mathbb{E}q$. Thus the expected price paid conditional on becoming uninformed must be $\mathbb{E}q$ for all bids made by uninformed bidders in any symmetric PBE in which $\sigma(\hat{b}) = 0$.

Now suppose $\sigma(\hat{b}) > 0$. Then (due to the tie breaking rule) the expected price paid when bidding $\hat{b}$ is a convex combination of the expected prices paid in the limit of sequences of bids converging to $\hat{b}$ from above and from below. But when making any bid below $\hat{b}$, a bidder always loses when an uninformed type is present, always pays q when an informed type is present, and thus has an expected price of $\mathbb{E}q$. Thus for her to be willing to bid $\hat{b}$ (rather than below or slightly above), she must be indifferent between bidding below $\hat{b}$ and the limit of bids converging to $\hat{b}$ from above. Thus the expected price for an uninformed player who bids $\hat{b}$ must be $\mathbb{E}q$ in a symmetric equilibrium; thus an uninformed player's expected price given any bid in Q must be $\mathbb{E}q$. □

Lemma 4. *When $n = 2$, in any symmetric PBE, uninformed bidders bid $\mathbb{E}q$ with probability of 1.*

Proof. Consider an arbitrary symmetric PBE. Summarize the probability distribution over other players' bidding strategy when uninformed by cumulative distribution function H, and let ρ denote the ex ante probability that each other player becomes informed. Then, the expected price to a given uninformed bidder of bidding b_i is given by:

$$(1-p)\left[\int_{\underline{q}}^{b_i} bdH(b) + (1 - H(b_i))\mathbb{E}q\right] + \rho\mathbb{E}q$$

This is weakly decreasing in b_i when $b_i < \mathbb{E}q$ and weakly increasing in b_i when $b_i > \mathbb{E}q$ and when compared to bidding $b_i = \mathbb{E}q$, any bid $b_i' < \mathbb{E}q$ must yield a strictly higher expected price whenever H assigns positive probability to to the interval $[b_i', \mathbb{E}q)$. Thus H must assign a probability of zero to bids below $\mathbb{E}q$. By a similar argument, H must assign a probability of zero to bids above $\mathbb{E}q$. Thus, uninformed bidders must bid $b^\star = \mathbb{E}q$ with a probability of one in any symmetric PBE. □

B Screenshots and Instructions

B.1 Screenshots

Below we include screenshots of the sequence of decisions made by subjects. At the end of the market, a new market started over and went through an identical sequence until all 16 markets were complete.

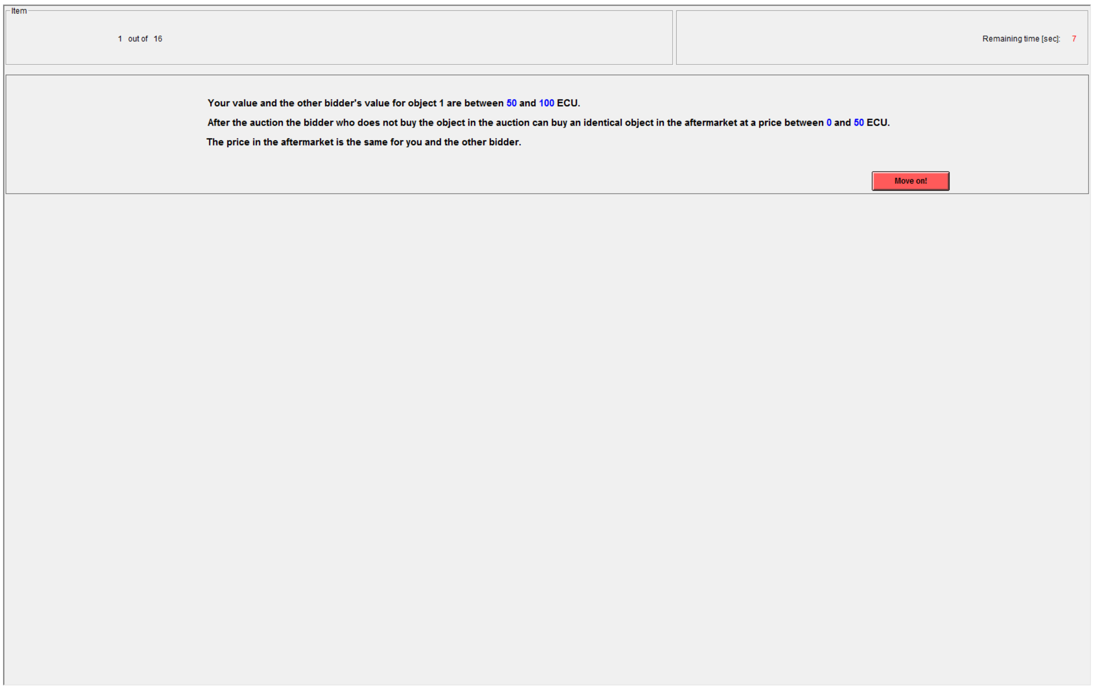

Figure B1: Screenshot of basic information

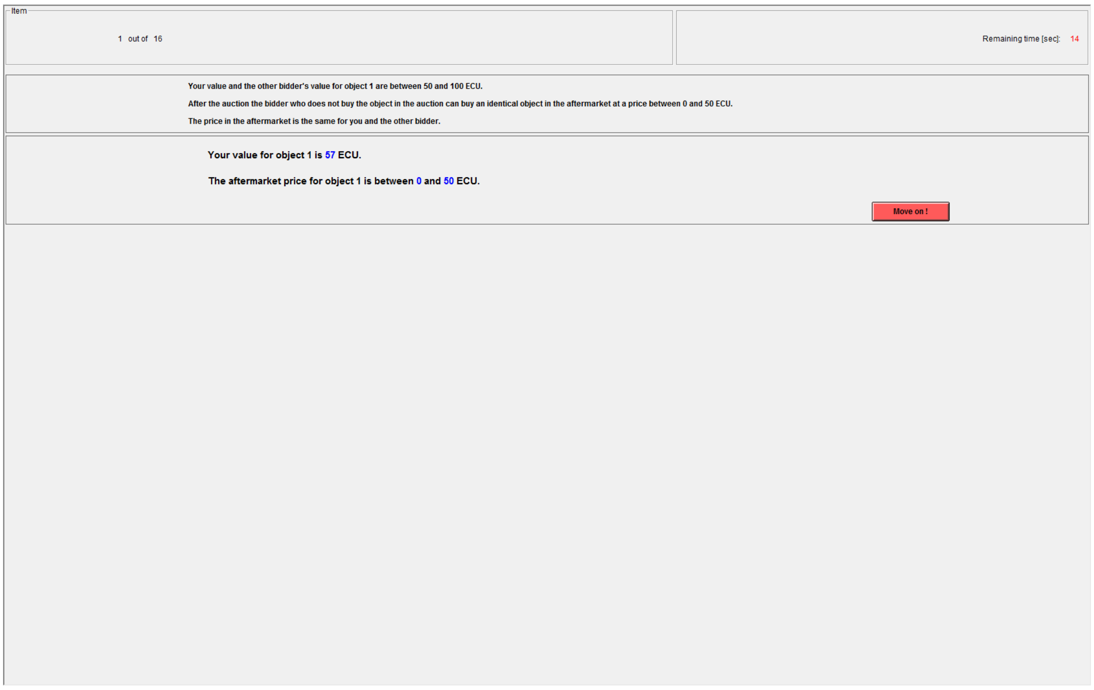

FIGURE B2: Screenshot of bidder value information

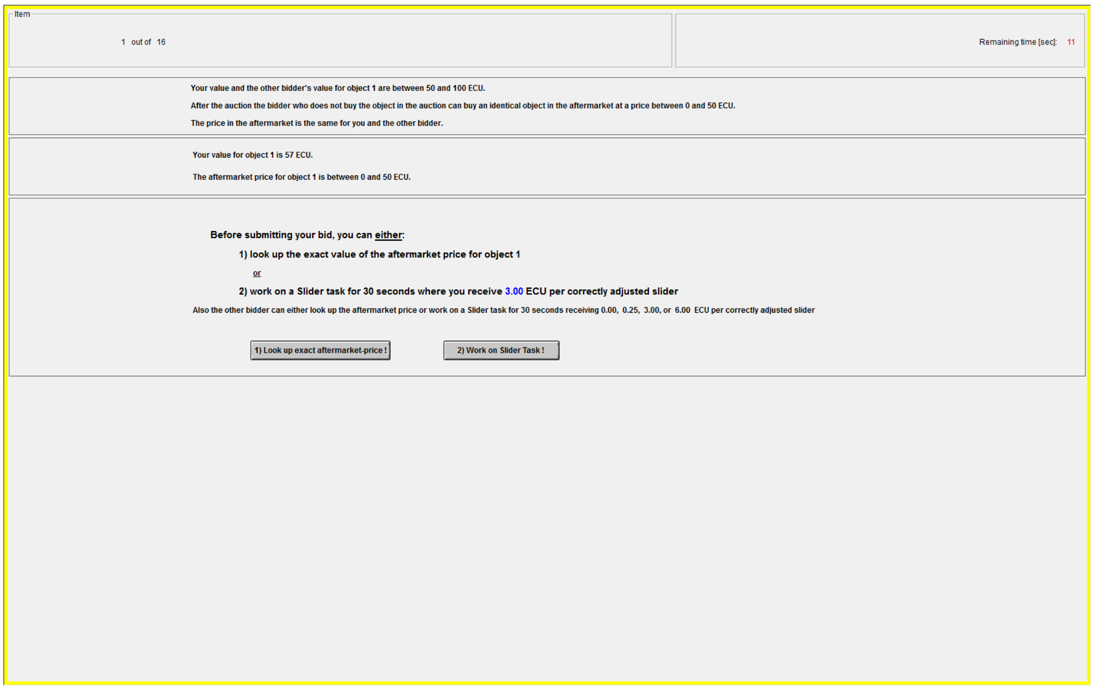

FIGURE B3: Screenshot of information acquisition decision

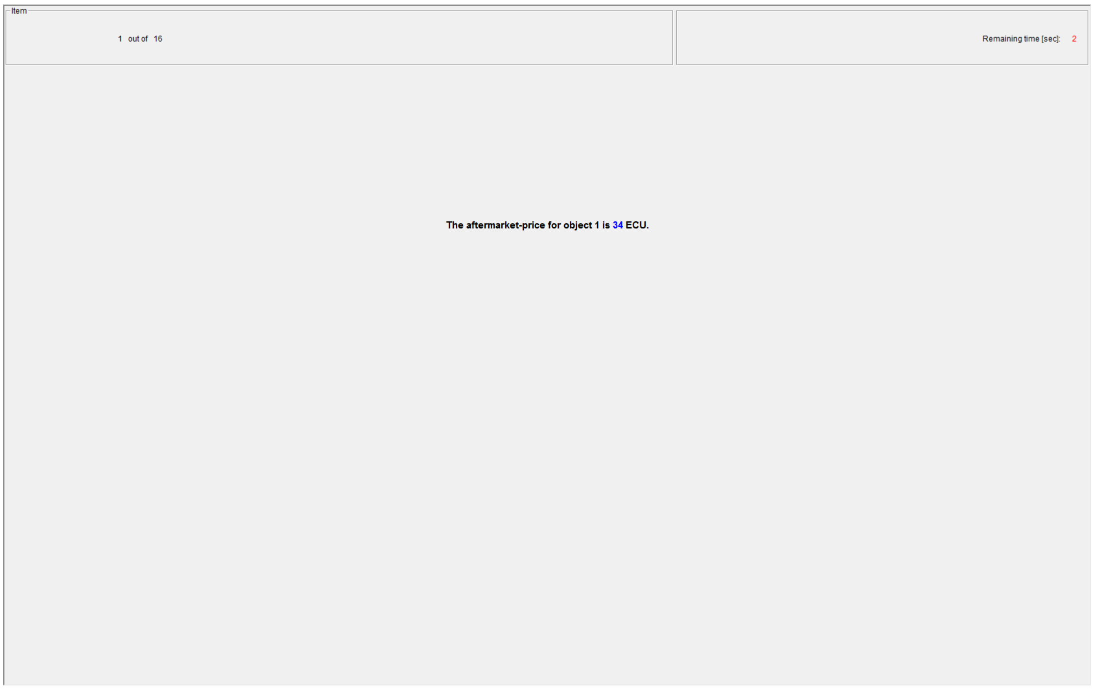

FIGURE B4: Screenshot for bidders who lookup the aftermarket price

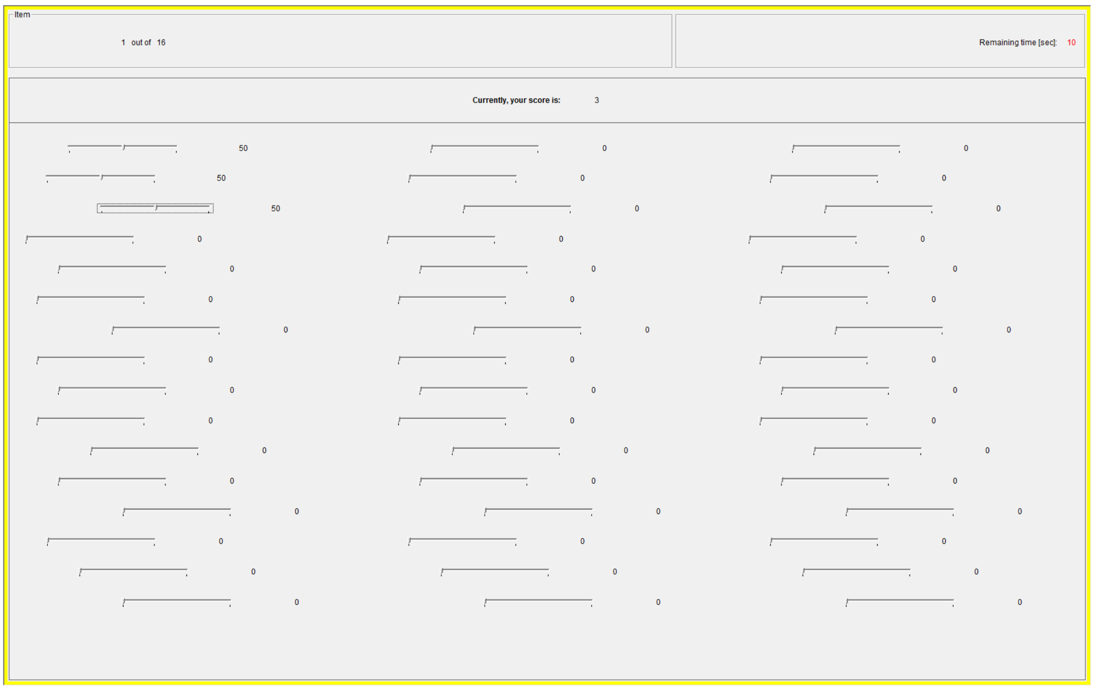

FIGURE B5: Screenshot for bidders who choose the slider task

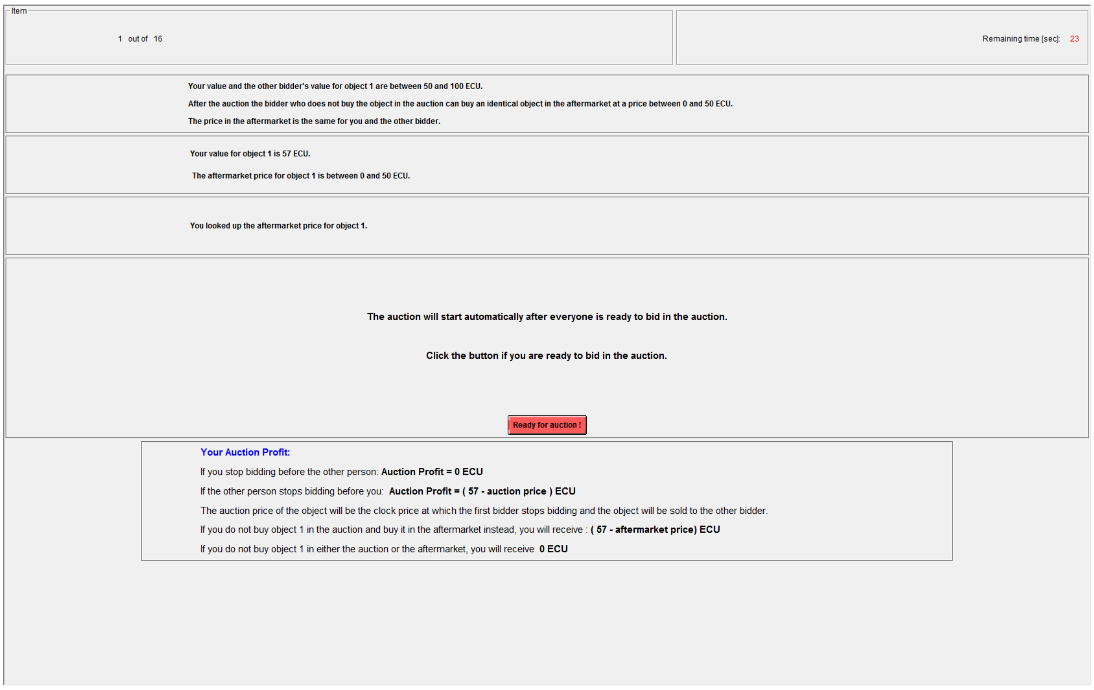

FIGURE B6: Screenshot of preliminary auction information

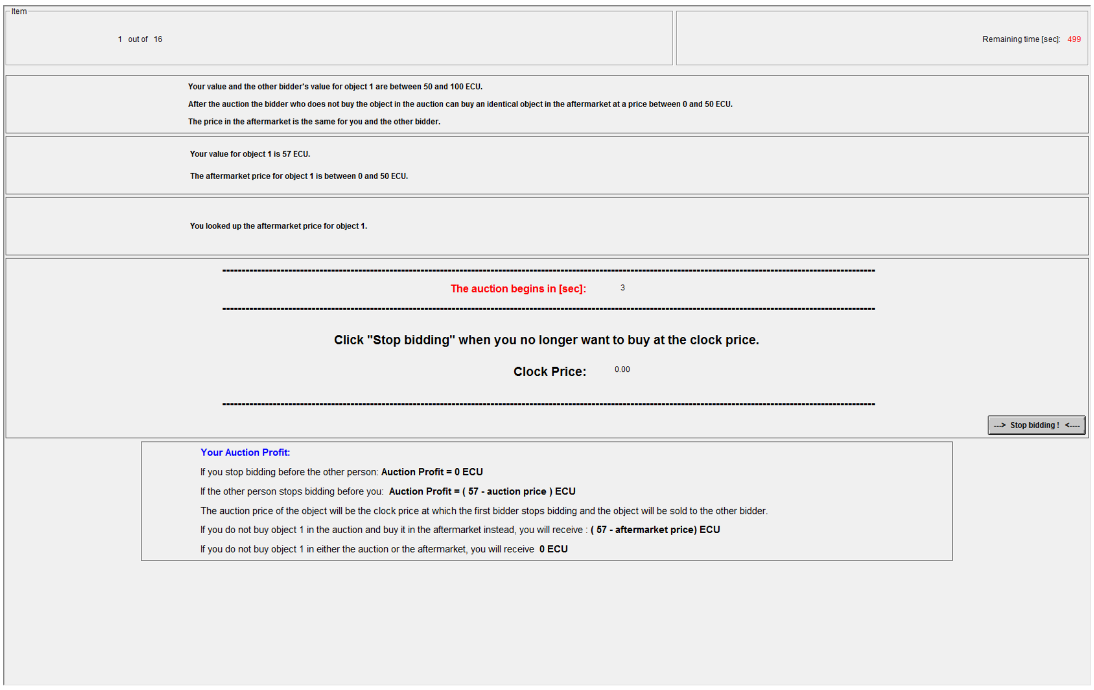

FIGURE B7: Screenshot before the clock starts ticking

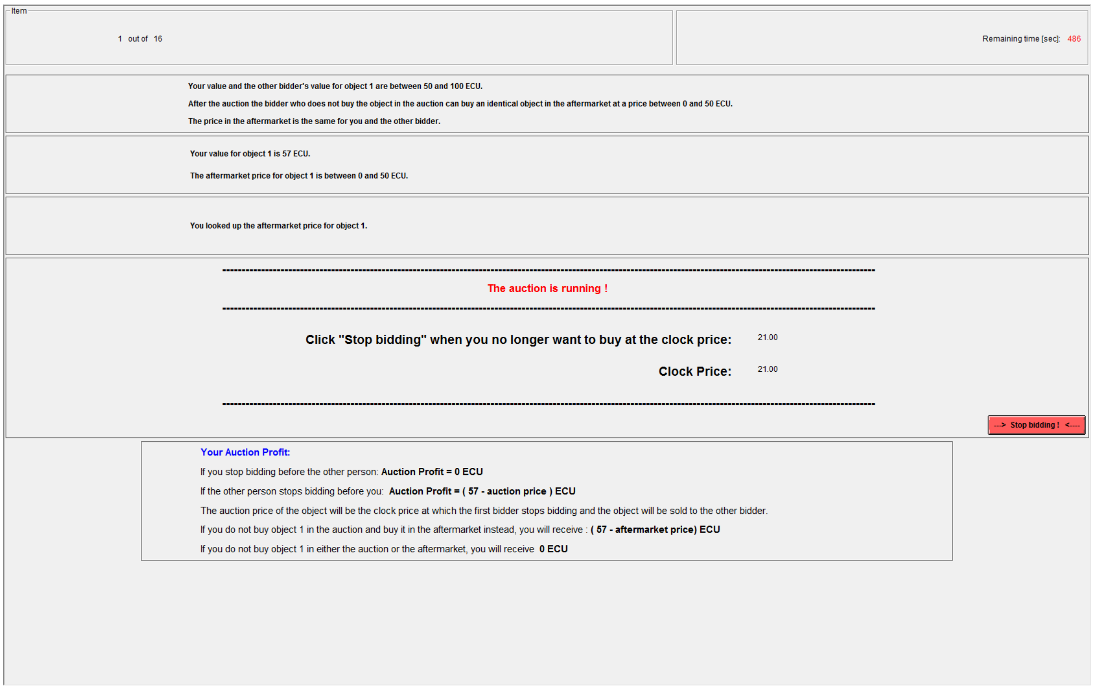

FIGURE B8: Screenshot of an active bidder during the auction

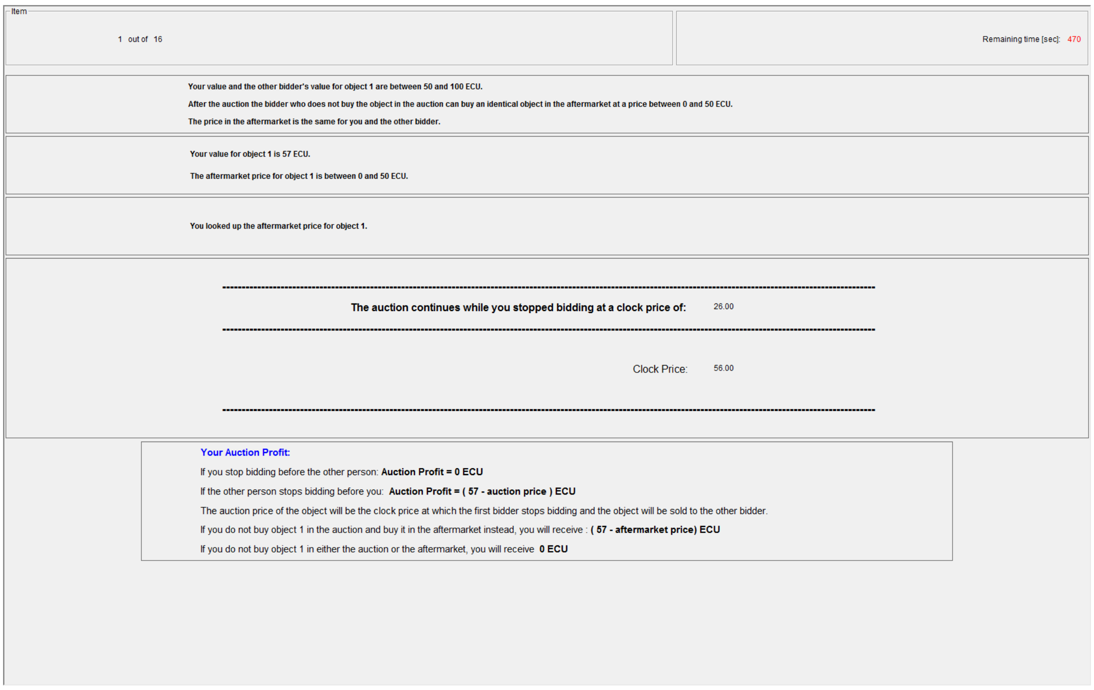

FIGURE B9: Screenshot after dropping out of the auction

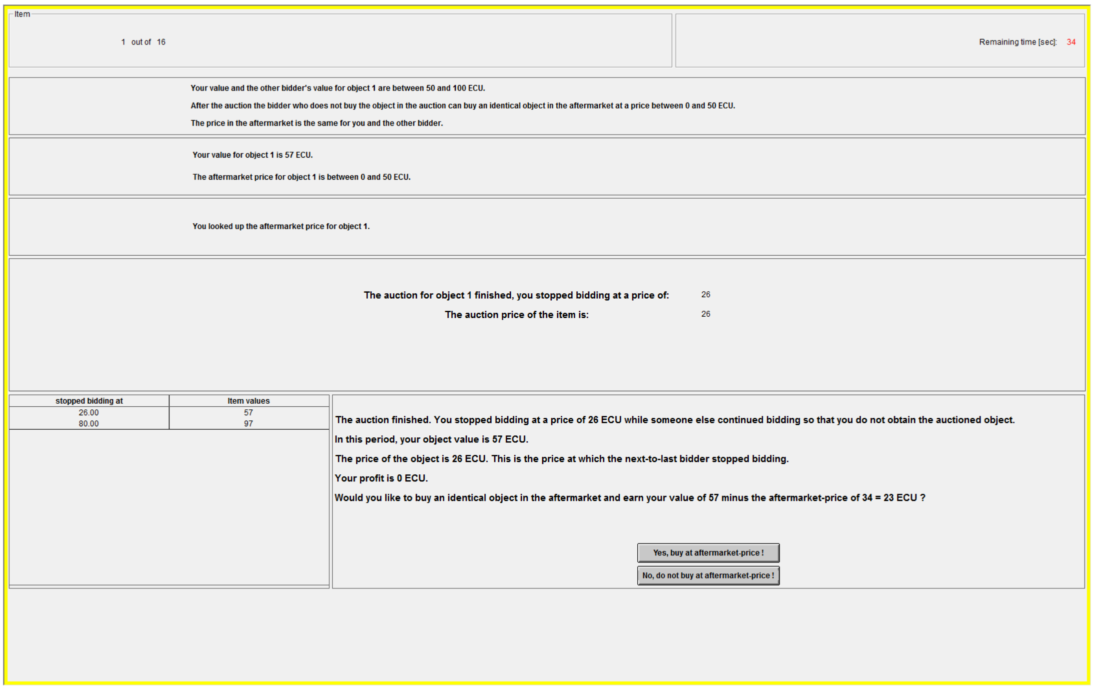

Figure B10: Screenshot of the aftermarket for the auction loser

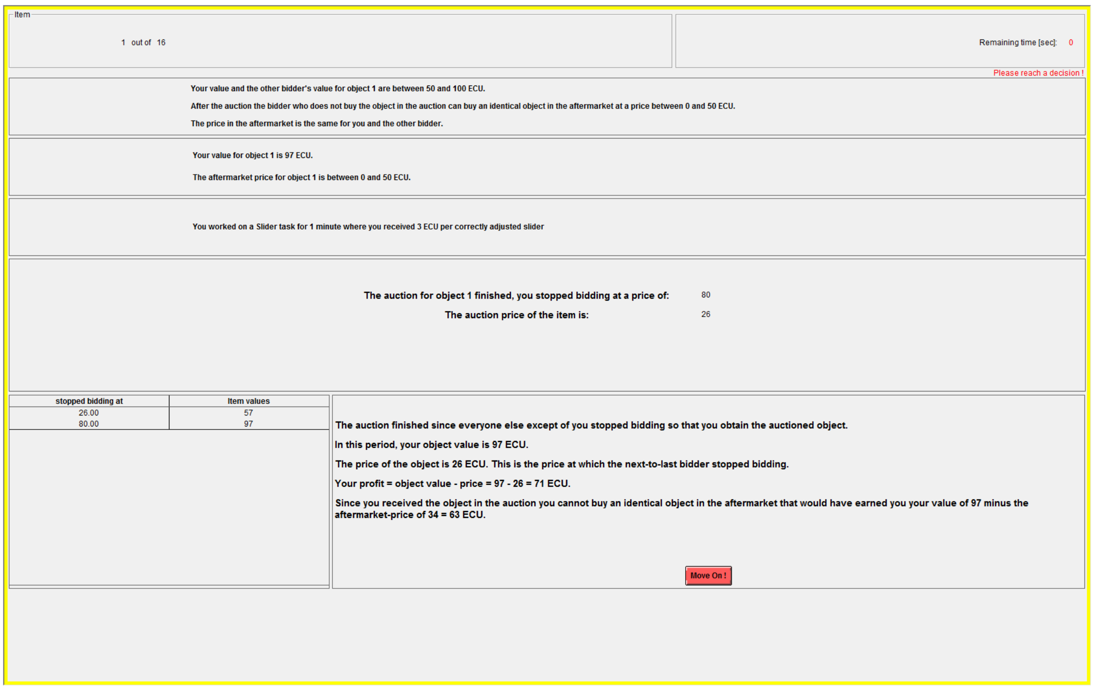

Figure B11: Screenshot summarizing the outcome for the auction winner

B.2 Instructions

General information

You are now participating in a decision making experiment. If you follow the instructions carefully, you can earn a considerable amount of money depending on your decisions, the decisions of the other participants, and an element of chance.

This set of instructions is for your private use only. **During the experiment you are not allowed to communicate with other participants**. If you have any questions, please raise your hand, and we will come to your seat and answer privately. Any violation of this rule excludes you immediately from the experiment.

During the experiment the outcome of your decisions will be measured in ECU (Experimental Currency Units) instead of Dollars. We will convert your total earnings into Dollars at a rate of 10 ECU = 1 Dollar at the end of the experiment and pay you in cash privately.

Outline of the Experiment

This experiment consists of 16 periods in which you can buy a fictitious object in either an **auction market** or an **aftermarket**. Each fictitious object will have some "value" to you – **you can think of your value as the amount of money (in ECU) that the experimenter will pay you for the object if you buy it**. So, if you have a value of 80 ECU for the object, and you buy it at a price P, you will earn 80 minus the price (80 – P) ECU.

In each period, your value will be a random whole number between 50 and 100 ECU. Each value is equally likely. **You will have a new random value in each period.**

The period starts with an auction. There are 2 bidders in each auction, you and someone else. **The other person bidding with you in each auction will change randomly**.

Other people also receive random values between 50 and 100 ECU for each object (with each value being equally likely), and all values are determined independently of one another. **You will only know your own value**, **and the other person in your auction will only know his/her own value**.

At the end of each auction, the **person who submitted the highest bid receives the object**. If there is a tie for the high bid, the object is assigned to one of the bidders by chance.

If you do not submit the highest bid, then you will not receive the object in the auction. However, anyone who did not buy the object in the auction **can buy an identical object after the auction at a fixed price that is the same for you and the other person in your auction. This price is called the *aftermarket price*, and it will be any number between 0 and 50 ECU where each number is equally likely**. Since the object for sale at the aftermarket price is identical to the auctioned object, **you have the <u>same value for it as for the auctioned object.</u>**

So, if your value is 80 ECU, and the aftermarket price is 42 ECU, and you choose to buy the object after the auction, you would receive 80 – 42 = 38 ECU.

Before these 16 periods you will participate in 3 rounds of a "Slider Task" in which you earn money by manipulating objects on the computer screen. You will be paid for your performance in the 3rd round of the "Slider Task".

You start off the experiment with an endowment of 70 ECU, which corresponds to your show up payment. At the end of the experiment, we will pay you the total of your earnings from the Slider Task plus your earnings from 1 *randomly chosen* period. This plus your Slider Task earnings will be added to your show-up payment and paid to you in **cash** at the end of the experiment.

Stage 1: The Slider Task Stage

The *Slider Task* stage allows you to earn money from a computerized task.

You will now participate in 3 rounds of an identical task **lasting 120 seconds per round** with a break of 60 seconds between each round. Rounds 1 and 2 allow you to practice the task and will not affect your earnings. The score that you will have obtained in round 3 will be used for determining your total earnings from the Slider Task Stage.

The task will consist of a screen with **48** sliders. Each slider is initially positioned at **0** and can be moved as far as **100**. Each slider has a number to its right showing its current position.

You can use the mouse or the keyboard's arrow keys in any way you like to move each slider. To use the arrow keys you have to select the slider that you want to adjust first by clicking it with the mouse. You can readjust the position of each slider as many times as you wish. You adjust the sliders to earn points. Specifically, y**our "score" in the task will be the number of sliders positioned at exactly 50 at the end of the 120 seconds**.

Your score in round 3 will be converted to ECU at a rate of **1 point = 1 ECU**. For example, if after 120 seconds you have correctly placed 6 sliders at 50, then you have earned 6 points, which is converted to 6 ECU and will be paid to you at the end of the experiment.

Thus your Slider Earnings are equal to (Your Score in the third round x 1 ECU)

Are there any questions?

Stage 2: The *Market* Stage

Each period consists of two parts, the *Auction* and the *Aftermarket*.

In the *Auction*, each person **bids** for the fictitious object. Before bidding, you will learn your **value**, and you can *either:*

1) Look up the **aftermarket price** for 30 seconds before submitting your bid

   OR

2) Participate in a 30-second round of the **Slider Task** to earn ECUs.

If you choose to look up the aftermarket price, you **cannot** participate in the Slider Task**,** but for 30 seconds you will see the aftermarket price of an identical object that you can buy in the *Aftermarket* if you do not receive the object in the auction.

If you choose to **participate in the Slider Task**, you will earn additional ECU based on your score from correctly adjusting sliders to 50, but *cannot* look up the **aftermarket price** before **bidding**. The amount of ECU that you receive per correctly adjusted slider will change over the 16 auctions, and you will be informed about it before you choose whether to participate in the task. Before each auction, the slider rate is chosen independently for each bidder with equal probability from 0, 0.25, 3, or 6 ECU per slider.

The other person in your auction can also either look up the aftermarket price or participate in the Slider Task, but they may earn more, less or the same amount per correctly adjusted slider as you.

At the end of 30 seconds, the bidding will begin. Your **value** will be displayed again. Below, in the auction panel, you will see a price called the **clock price**. The clock price will start at **0 ECU**, and will increase by **1 ECU** with each tick of the clock. The bidding starts immediately, and **your bid is equal to the clock price**. You can stop bidding and leave the auction by clicking the "Stop Bidding" button next to the clock price. Similarly, the other bidder can stop bidding and leave the auction. You remain actively bidding as long as you have not yet clicked "Stop Bidding".

Neither bidder will observe whether the other bidder has stopped bidding. **If the other bidder leaves the auction while you continue bidding, the market price of the object is the clock price at which the other bidder stopped bidding**, although you continue to see the clock price increasing until you stop bidding. Similarly, if you stop bidding while the other bidder continues, the market price of the object is the clock price at which you stopped bidding.

After you and the other person in your auction both click "Stop Bidding", you will see the outcome of the auction. The bidder who continued to bid longer and higher in the auction (the high bidder) gets the object and receives **Auction Earnings** equal to the difference between the object's value and the price of the object; the other bidder receives no Auction Earnings, that is:

- if you are the high bidder:
    - Your Auction Earnings = (Your **value – market price**) ECU

    If this difference is negative because the price exceeds the object's value, then the Auction Earnings of the high bidder are negative, which represents a loss.

- if you are not the high bidder:
    - Your Auction Earnings = 0 ECU

If you stop bidding at the same price as the other bidder, chance decides who gets the object, and the price is equal to the clock price at which you both stopped bidding. If no one stops bidding before the clock price reaches 105 ECU, then the object will be allocated by chance at a price of 105 ECU.

If you are the high bidder so that you receive the auctioned object, you **do not** participate in the *Aftermarket*. However, if you are not the high bidder, you can buy an **identical object** in the *Aftermarket*.

In the *Aftermarket*, you will be reminded of your **value** for the object (which is exactly equal to your value for the auctioned object) and the **aftermarket price**. If you want to buy the object at the aftermarket price, click the button labeled "Buy". Your Aftermarket Earnings are determined as follows:

- if you choose to buy the object in the aftermarket:
    - Your Aftermarket Earnings = (your **value** – **aftermarket price**) ECU
- if you choose *not* to buy the object in the aftermarket:
    - Your Aftermarket Earnings = 0 ECU

At the end of the *Aftermarket*, one period is complete.

Your Stage 2 Earnings

Your **Earnings** for an individual period can be determined in one of the following six ways:

1) You receive the object in the auction, and you participate in the Slider Task

   Earnings = (your **value – market price** + Slider Task Earnings) ECU

2) You receive the object in the auction, and you *do not* participate in the Slider Task

   Earnings = (your **value – market price**) ECU

3) You do not receive the object in the auction, you participate in the Slider Task, and you choose to buy an object in the Aftermarket.

   Earnings = (your **value – aftermarket price** + Slider Task Earnings) ECU

4) You do not receive the object in the auction, you *do not* participate in the Slider Task, and you choose to buy an object in the Aftermarket.

   Earnings = (your **value** – **aftermarket price**) ECU

5) You do not receive the object in the auction, you participate in the Slider Task, and you choose *not* to buy an object in the Aftermarket.

   Earnings = Slider Task Earnings ECU

6) You do not receive the object at auction, you *do not* participate in the Slider Task, and you choose *not* to buy an object in the Aftermarket.

   Earnings = **0** ECU

Total Earnings

Now we will do 2 practice auctions, to familiarize you with the interface. These will not count for payment. After the practice, we will restart the experiment. At the end of the experiment, we will randomly draw **1 out of the 16 periods** for payment. If your stage 2 earnings are positive, then your ECU balance increases by this amount. If your earnings are negative, you made a loss and your ECU balance decreases by the amount of the loss. If your earnings are 0 ECU, then your ECU balance does not change. Finally, we will add your earnings from the *Slider Task* stage (Stage 1) to your ECU balance and we will convert it to Dollars at a rate of 10 ECU = 1 Dollar. When the experiment is over, please wait quietly until we call you for payment.

C Additional Data Analysis

C.1 Full Probit Estimates from Sections 4.1 - 4.3

Tables C1, C2, C3 and C4 report complete estimates from the regression analyses reported in Sections 4.1, 4.2 and 4.3, respectively. In all three models, standard errors are clustered at the session level.

In Table C1 we regress an individual bidder's decision to lookup the aftermarket price on the value of k, controlling for the bidder's value (v_i) and the market period.

	Lookup
v_i (value)	0.00434
	(0.00282)
k (opportunity cost)	-0.433***
	(0.0378)
Period	-0.00115
	(0.00684)
Constant	0.694**
	(0.274)
Log Lik.	-452.274
N	1024

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C1: Probit regression analysis of the lookup decision, from Section 4.1.

In Table C2 estimate a probit regression in which the dependent variable is a dummy that takes a value of 1 if a subject's lookup decision was rationalizable and 0 otherwise. The independent variables include a dummy for the second half of the experiment to test whether decisions become more rationalizable with experience as well as dummies for $k = 0.25, 3$, and 6, with $k = 0$ the excluded group. The estimates reveal that rationalizable decisions are not statistically significantly more likely in the second half of the experiment than in the first half, suggesting that experience is not an important factor in our design. Interestingly, the coefficients on the two dummies for $k = 0.25$ or $k = 3$ are negative and significant; suggesting that rationalizable decisions are somewhat less likely in these more difficult decisions than in the simpler decisions when $k = 0$ or $k = 6$.

In Table C3 the dependent variable is a dummy indicator for whether an individual bid exceeded the aftermarket price. We regress this on a dummy variable that takes a value

	Rationalizable (No)Lookup
$k = 0.25$	-0.423**
	(0.190)
$k = 3$	-0.692**
	(0.270)
$k = 6$	-0.101
	(0.270)
Second Half (period > 8)	0.103
	(0.095)
Constant	1.426***
	(0.180)
Log Lik.	-377.475
N	1024

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C2: Probit regression analysis of the rationalizability of the (no)lookup decision, from Section 4.1.

of 1 when the bidder looks up the aftermarket price and 0 otherwise. We also control for the bidder's value (v_i) and the market period. Note that v_i is also statistically significant in this regression suggesting that bidders with higher values are more likely to overbid; this is perhaps consistent with intuition that such overbiding is less costly to those with higher values.

	Overbid (relative to q)
v_i (value)	0.00874***
	(0.00207)
Lookup	-0.631***
	(0.111)
Period	-0.00655
	(0.0118)
Constant	-0.387*
	(0.214)
Log Lik.	-669.559
N	1024

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Probit regression analysis of overbidding (relative to the aftermarket price), from Section 4.2.

In Table C4 the dependent variable is a dummy indicator for whether the auction price in a market exceeded the aftermarket price. The right hand side variables include dummy indicators for the cases in which 1 or both bidders look up the aftermarket price before bidding (with both bidders remaining uninformed as the excluded group), as well as a control for the market period.

	Overpay (relative to q)
$N_{lookup} = 1$	-0.386*
	(0.218)
$N_{lookup} = 2$	-1.122***
	(0.148)
Period	-0.0190
	(0.0164)
Constant	-0.176
	(0.150)
Log Lik.	-257.367
N	512

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C4: Probit regression analysis of overpaying (relative to the aftermarket price) aka the Bidder's Curse, from Section 4.3.

C.2 Estimating the probability of overbidding, conditional on the decision to lookup

Since an individual's likelihood of overbidding relative to the aftermarket price is a function of their (endogenous) decision to lookup the fixed price, it may be important to account for self-selection when examining the impact of remaining uninformed on overbidding. Thus, to complement our estimates from section 4.2 we estimate a system of two seemingly unrelated probit equations. In the first equation, the dependent variable λ takes a value of 1 if the bidder chose to lookup the fixed price and a value of 0 otherwise; the independent variables include a constant term, and the expected earnings of the slider task (computed as the product of the piece rate, k_t, and the number of sliders a subject correctly placed in part I (Productivity Measurement), e_i^I, which measures individual productivity at the slider task). In the second equation, the dependent variable θ takes a value of 1 if a bidder bid more than the fixed price in the auction and 0 otherwise. The independent variables are a dummy variable indicating whether the subject chose to lookup the fixed price and a subject's value for the item. We also include a control for the fixed price, since overbidding should be less likely, the higher is the fixed price. In both equations, standard errors are clustered at the subject level to control for heteroskedasticity.

$$\lambda_i = \alpha_0 + \alpha_1 k_{i,t} e_i^I + \epsilon \tag{8}$$

$$\theta_i = \beta_0 + \beta_1 \lambda_{i,t} + \beta_2 v_{i,t} + \beta_3 q_t + \epsilon \tag{9}$$

Table C5 displays the output of the regression; one session is excluded from the regression because a software error left us without an estimate of productivity for those subjects (e_i^I).[29] As noted above, in equation (7) the estimated coefficient on $k_t \times e_i^I$ is negative and significant indicating that the probability of looking up the fixed price decreases with a subject's opportunity cost. Moreover, in equation (8), a negative and significant estimated coefficient on the decision to lookup the fixed price indicates that overbidding is significantly driven by opportunity cost. When bidders choose to lookup the price, they are significantly less likely to overbid than when they instead choose to participate in the slider task.

C.3 Estimates of a QRE model of bidding behavior

To investigate the extent to which noisy behavior can explain observed dispersion in bids and overbidding, we estimated a QRE model of bidding behavior, taking information acquisition decisions as a given. In our QRE model, each agent noisily chooses among strategies, with a greater tendency to choose strategies with higher expected payoffs, given the behavior of other agents. We model a player's behavior in the aftermarket as governed by a separate and independent agent (as in "Agent-Based QRE"; see section 3.2 in Goeree et al., 2016). Behavior is assumed to follow a logit form, with the parameter α capturing the degree of noisiness. Our model assumes that heterogeneity in behavior, given an agent's information, arises only due to random variation, rather than underlying individual differences – which gives us a one-parameter generalization of the standard

[29] Our results are robust to including that session and replacing $k_{i,t} e_i^I$ with $k_{i,t}$ in the selection equation. Estimates available upon request.

	Estimates
Eq. 7: Lookup	
Expected Earnings	-0.029***
(k × e_i^I)	(0.003)
Constant	0.952***
	(0.131)
Eq. 8: Overbid	
Lookup ($\lambda_{i,t}$)	-0.679***
	(0.180)
Value ($v_{i,t}$)	0.010***
	(0.003)
Posted Price (q_t)	-0.037***
	(0.004)
Constant	0.356
	(0.249)
Log Lik.	-872.059
N	896

Clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C5: Bivariate probit regression explaining the probability of looking up the aftermarket price and the probability of overbidding.

theory in section 2.[30]

In the aftermarket, an agent with valuation v who faces aftermarket price q buys the object with probability

$$p(v, q|\alpha) = \frac{\exp\left(\alpha\left(v - q\right)\right)}{\exp\left(\alpha\left(v - q\right)\right) + \exp\left(0\right)} \tag{10}$$

and otherwise does not buy.

Let $i \in \{50, \ldots, 100\} \times (\{0, \ldots, 50\} \cup \{\text{uninformed}\})$ denote a player's information, which consists of her valuation of the object and either knowing the aftermarket price or being uninformed. Let ρ denote the fraction of the time that each agent becomes informed, which we take as exogenous for the purpose of this exercise.[31] Let σ', p' denote the stochastic response functions in the auction and aftermarket played by other agents, and let $U(b|i)(\sigma', p')$ denote the expected utility of bidding b given the behavior of other

[30] An extension of the model that allows α to vary between informed and uninformed agents yielded very similar estimates of α for both.

[31] Note that, due to the logit functional form, this model predicts that earnings from the slider task will not affect subsequent behavior in the auction and aftermarket.

agents. Then, assume a player's probability of making bid b given information i is given by:

$$\sigma(b,i|\alpha) = \frac{\exp\left(\alpha U\left(b,i\right)\left(\sigma',p'\right)\right)}{\sum\limits_{b'=0}^{105}\exp\left(\alpha U\left(b',i\right)\left(\sigma',p'\right)\right)} \tag{11}$$

The value of $U(b|i)(\sigma',p')$ is given by:

$$\begin{aligned} & U(b|(v,q))(\sigma',p') = \\ & \quad \rho\Bigg(\frac{1}{51}\sum_{v'=50}^{100}\Bigg[\sum_{b'=0}^{b-1}\sigma'(b'|(v',q))\,(v-b') + \frac{1}{2}\sigma'(b|(v',q))\,(v-b) \\ & \quad +\Bigg(\frac{1}{2}\sigma'(b|(q,v')) + \sum_{b'=b+1}^{106}\sigma'(b'|v',q)\Bigg)p'(v,q)\Big(v-q\Big)\Bigg]\Bigg) \\ & + \quad (1-\rho)\Bigg(\sum_{b'=0}^{b-1}\sigma'(b'|(v',\text{uninformed}))\,(v-b') + \frac{1}{2}\sigma'(b|(v',\text{uninformed}))\,(v-b) \\ & \quad +\Bigg(\frac{1}{2}\sigma'(b|(q,v')) + \sum_{b'=b+1}^{106}\sigma'(b'|v',\text{uninformed})\Bigg)p'(v,q)\Big(v-q\Big)\Bigg) \end{aligned} \tag{12}$$

$$\begin{aligned} & U(b|(v,\text{uninformed}))(\sigma',p') = \\ & \quad \rho\Bigg(\frac{1}{51}\sum_{q=0}^{50}\frac{1}{51}\sum_{v'=50}^{100}\Bigg[\sum_{b'=0}^{b-1}\sigma'(b'|(v',q))\,(v-b') + \frac{1}{2}\sigma'(b|(v',q))\,(v-b) \\ & \quad +\left(\frac{1}{2}\sigma'(b|(q,v')) + \sum_{b'=b+1}^{106}\sigma'(b'|v',q)\right)\,p'(v,q)\Big(v-q\Big)\Bigg]\Bigg) \\ & + \quad (1-\rho)\left(\sum_{b'=0}^{b-1}\sigma'(b'|(v',\text{uninformed}))\,(v-b') + \frac{1}{2}\sigma'(b|(v',\text{uninformed}))\,(v-b)\right. \\ & \quad \left.+\left(\frac{1}{2}\sigma'(b|(q,v')) + \sum_{b'=b+1}^{106}\sigma'(b'|v',\text{uninformed})\right)\,\frac{1}{51}\sum_{q=0}^{50}p'(v,q)\Big(v-q\Big)\right) \end{aligned} \tag{13}$$

A strategy $\sigma^\star, p^\star$ is an equilibrium when $p^\star$ is given by (10), and given $U(b,i)(\sigma^\star,p^\star)$ computed according to (12 and 13), $\sigma^\star$ is consistent with (11).

QRE model fit	
$\hat{\alpha}$	.46
s.e.	.02

Table C6: Estimated α from the QRE Model

We constructed a program in R (2015) to find the QRE strategies σ^α and p^α corresponding to α as follows. By Proposition 3.1 in Goeree et al. (2016), a QRE exists in our problem. Our program starts with random behavior, and then iteratively solves for the response functions using (2) until strategies have converged. Notice that choice probabilities in this model are continuous in utility and in α, and utility is in turn continuous in the strategy of other agents. As a result, the program will find strategies arbitrarily close to a QRE.[32]

Given σ^α, we can construct the contribution of a given bid to the likelihood function:

$$ll(b, i|\alpha) = \sigma(b, i|\alpha) \tag{14}$$

and given p^α, the contribution of an aftermarket decision to the likelihood function is given by:

$$ll(\text{buy}, v, q|\alpha) = p(v, q|\alpha) \tag{15}$$

$$ll(\text{don't buy}, v, q|\alpha) = 1 - p(v, q|\alpha) \tag{16}$$

We estimate α by maximum likelihood using the mle command.[33] Our results are reported in Table C6.

Table C7 compares the bidding predictions generated by our estimated QRE model against the core features of our bidding data that were reported in our results section. The estimates suggest that QRE can help account for some of our observations such as excess bid dispersion and on-average overbidding, especially among the uninformed. However, in some ways QRE predicts "too much" noise and fails to capture the relatively close adherence to dominant strategy bidding by the informed. We summarize the evidence

[32]We have not proven that the QRE is unique; by starting this process from uniform random behavior, our approach will select the "logit solution", which is common practice in estimating the QRE model (see Goeree et al., 2016, p. 152).

[33]Note that the standard errors displayed assume that each observation (i.e. each bid and each aftermarket decision) is independent. Since we are not primarily interested in inference about α, we do not make corrections to account for interdependencies among observations.

Deviation of bids from point predictions	Uninformed	Informed
+-1	7.8% (11.7%)	11.8% (30.8%)
+-5	27.8% (30.4%)	38.7% (54.7%)
+-10	49.4% (51.2%)	61.1% (70.2%)
median	27 (30)	26 (25)
average	30.2 (32.4)	29.9 (27.0)

TABLE C7: Model-predictions of the % of bids for a given information type that fit within specified bounds of the PBE point predictions; corresponding figures from data in brackets

below.

Notice that overbidding is substantially more pronounced by uninformed bidders relative to informed bidders, and uninformed bidders also appear noisier relative to the PBE predictions: informed bidders are substantially more likely to bid close to the PBE point prediction. In the model, this can only arise out of weaker payoff incentives for uninformed than for informed bidders to adhere to the PBE strategy. It appears that overbidding is driven by the conjunction of noisy behavior and a strategy space that always contains more bids above the PBE point prediction than below. Since noise in the QRE model generates a positive probability of making each possible bid, it tends to produce more overbidding than underbidding both on average and at the median; since uninformed bidders have weaker incentives and make more dispersed bids, they tend to overbid more than informed bidders; see Figure 8 in the main text.

Our baseline QRE model does not capture the very-close adherence to the dominant strategy by a large fraction of informed bids. Instead it predicts noisy behavior more continuously about those predictions. One possible explanation is that bidding around the aftermarket price is salient and/or cognitively easy to identify for some subjects when informed. Adding heterogeneous types as in HQRE (see section 4.2 in Goeree et al., 2016) only slightly improves the model fit; estimates available upon request.

We also note that the estimated model actually underestimates the frequency at which subjects fail to buy when in the aftermarket, predicting that players who reach the aftermarket only fail to buy 0.2% of the time (while players fail to buy 5.7% of the time in our data). This suggests that, in the estimated model, the anticipation of potentially failing to buy in the aftermarket does not drive much overbidding (nor differential overbidding).