Experimental Auctions with Securities*

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This Version: June 18, 2024

First Draft: August 4, 2022

Abstract

We experimentally implement security-bid auctions, which are used around the world to sell projects that generate large future cash flows that are stochastic. Buyers make bids with debt and equity, linking payments to the project's ex-post revenue. Contrary to the theoretical predictions, we find that debt auctions generate more revenue than equity auctions. This is explained by overbidding in debt auctions. Furthermore, we find that second-price equity auctions generate slightly more surplus than other treatments. We also implement informal auctions and find that buyers use equity more often than theory predicts, and that sellers successfully choose dominant bids.

JEL classification: C70, C90, D44, D47

Keywords: auctions; experiment; securities; debt; equity; risk preferences

*We thank Danelle Kenny for her excellent research assistance. We are grateful for comments from Marina Agranov, Ned Augenblick, Evan Calford, Tim Cason, Marco Faravelli, Paul Feldman, Guillaume Fréchette, Lana Friesen, Tanjim Hossain, Nagore Iriberri, Gregory Kubitz, Tracy Xiao Liu, Claudio Mezzetti, John Morgan, Ryan Oprea, Siqi Pan, Paul Pezanis-Christou, Andrew Schotter, Jason Shachat, Charles Sprenger, Tom Wilkening, and Leeat Yariv, as well as audiences at ANU, ANZWEE, Chapman University, ESA North America, OEW, QUEX, QUT, Texas A&M, the University of Melbourne, and UQ. The informal auctions treatment from this paper was presented as Hunt's honours thesis at the University of Queensland prior to Hunt commencing employment at the Reserve Bank of Australia. The experiments discussed in this paper received ethical approval from UQ's BEL LNR review panel (project numbers 2021/HE000019 and 2021/HE001827). The formal auction treatments in this experiment were preregistered in the American Economic Association's RCT Registry (AEARCTR-0009157). The views expressed in this work are those of the authors and do not necessarily reflect the opinion of the Reserve Bank of Australia.

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1 Introduction

Security-bid auctions are used extensively around the world to allocate the rights to control projects (assets) that generate future cash-flow streams. For instance, governments use them to sell oil, gas, timber, and spectrum leases, and to allocate "build-operate-transfer" (BOT) contracts in public infrastructure; corporations use them to organize the market for takeovers and to finance capital ventures; and, finally, individuals use them to sell the rights to publish books and to set legal fees in lead plaintiff class-action suits. The distinctive feature of all these auctions is that the future revenue of the auctioned project can be verified ex-post, and, thus, can be contracted upon to securitize the seller's payment.

The way in which these auctions are organized can be either formal or informal. In the former, the seller commits to sell the project using a predetermined auction format and security design; whereas in the latter, buyers can choose their securities freely to signal their types and the seller allocates the project to the buyer that made the most attractive bid ex-post. The securities most commonly used in both types of auctions are the so-called "standard securities", among which are equity and debt. When a seller runs an auction in equity, each bid corresponds to a "fraction or share" of the future project's revenue. In turn, when the auction is run in debt, each bid corresponds to a "default level" that acts as a threshold such that if the project's revenue falls below the default level, the seller retains the entire revenue, otherwise, it only retains the default level.

While the theoretical literature on these auctions is extensive, few empirical studies explore their characteristics. These auctions are large and complex, and buyers must usually complete due diligence to simply make bids. Moreover, details on bids and valuations are sensitive because they can reveal crucial information about firms to their competitors. Thus, data on these auctions is normally restricted and there has been little systematic empirical analysis comparing selling mechanisms.

In this paper, we propose an experimental approach to evaluate how buyers behave when they face different selling mechanisms that vary in several dimensions. First, conditional on the mechanism being formal, we consider two auction formats: a first- and a second-price auction, and two different ordered sets of securities: debt and equity. The exogenous variation in the design allows us to disentangle how the auction formats and the securities used impact buyers' bidding behavior and the auction's revenue and efficiency. As such, we go beyond the experimental analysis of cash auctions that only tests the behavioral consistency of buyers across formats. Second, we implement an informal mechanism in which buyers can choose to submit their bids using either debt or equity (but not combinations thereof). Here, a third subject—acting as the seller—must choose which bid wins the auction. As in first-price auctions, the winner's payments are based on the winner's bid. In such mechanisms, there is not a clear-cut way to order bids when they are made using different securities. Thus, the seller must form beliefs about the revenue generated by each bid and choose the one with the highest value, which leads buyers to engage in a signaling game. We can test whether—and how—buyers engage in this type of behavior. Furthermore, unlike in formal auctions, where the allocation rule is predetermined, in informal auctions, we can also evaluate the seller's decision-making in the face of complex bids, a feature that is novel in the experimental auction literature.

Our empirical results do not coincide with the main predictions of the theoretical literature on security-bid auctions. Contrary to these predictions, we find that debt auctions raise more revenue than equity auctions. This is largely explained by the fact that buyers in debt auctions overbid relative to equilibrium predictions. The differences in efficiency between treatments are much smaller than the differences in revenue. Finally, we find that subjects in informal auctions make their bids using equity more often than debt, but otherwise conform closely to equilibrium predictions. The revenue raised by informal auctions is the lowest among the selling mechanisms studied, which is consistent with the prediction of the theoretical literature under risk-neutral buyers.

A motivating example The reason for which a security-bid auction might be preferred by a seller in formal mechanisms can be illustrated with a simple example introduced by Hansen (1985) and replicated by DeMarzo et al. (2005). Consider a second-price auction in which two buyers, Alice and Bob, compete for a project. The project requires an initial non-contractible investment of \$1M, which can be interpreted as the minimum upfront cash required by the seller. Alice expects that if she undertakes the project, it will yield her a net present value (NPV) of \$4M, whereas Bob expects an NPV of \$3M. We assume that both valuations are common knowledge to buyers. If the auction is run in cash, the weakly dominant strategy for both buyers is to bid their reservation value. As a result, Alice bids \$3M and Bob bids \$2M. Therefore, Alice wins the auction and pays Bob's bid of \$2M. Now, suppose that instead of bidding in cash, both buyers compete by offering equity over the project's NPV. In this case, bidding their reservation value is also a weakly dominant strategy for both buyers. Thus, Alice makes an equity bid of $\frac{\$4\text{M}-\$1\text{M}}{\$4\text{M}} = 3/4$ and Bob makes an equity bid of $\frac{\$3\text{M}-\$1\text{M}}{\$3\text{M}} = 2/3$. As a result, Alice wins the auction and pays according to Bob's bid, generating a revenue of $2/3 \times \$4\text{M} = \$2.67\text{M} > \$2\text{M}$. The reason why equity yields a higher revenue is that although the price is determined by the type of the losing buyer, the payment is determined using the winning buyer's type, creating greater linkage.[1]

[1] The same intuition holds for debt, but to illustrate its superiority over cash it would be necessary to use the full distribution of revenue's project (not only its NPV) because debt is non-linear.

Background In our economic setting, two buyers make bids to control the rights to a project with stochastic revenue. The project yields either a low payoff or a high payoff, and each buyer independently knows their personal likelihood of receiving the high payoff (i.e., they have independent and private values for the project). We consider five types of auctions: (1) first-price debt auctions, (2) first-price equity auctions, (3) second-price debt auctions, (4) second-price equity auctions, and (5) informal auctions. The first four types of auctions are formal mechanisms because the format and security design are predetermined: the rules of the auction dictate the security that bids are made in, which buyer wins the project, and the "price" that must be paid. The last type of auction is informal because buyers can freely choose between debt and equity to express their bids and the seller is not bound by any rule when choosing the winner.

Equity and debt are natural securities to study because they are ubiquitous in practical applications. For example, equities are used around the world to sell natural resources, whereas debts are used in BOT contracts and takeover operations. Additionally, both securities have clear theoretical predictions regarding revenue and efficiency that can be tested in the laboratory. Specifically, under equity, first- and second-price auctions satisfy revenue equivalence, whereas under debt, second-price auctions yield a greater expected revenue than the first-price. Moreover, the revenue under the second-price debt auction is lower than the revenue under any equity auction.

The reason auctions using equity yield greater revenue than those using debt is that the former creates a greater linkage between the winning buyer's underlying value and the seller's payment. Following DeMarzo et al. (2005)—henceforth DKS—we say that equity is *steeper* than debt, meaning that the slope of the payment, as a function of revenue, at the point where the two securities yield the same expected payment is higher for equity than debt. This allows equity to extract higher surplus from buyers with higher signals. Moreover, as shown by Fioriti and Hernandez-Chanto (2021), equity also provides greater insurance to risk-averse buyers, since it asks for lower payments when revenue is low and for higher payments when revenue is high. This insurance is relatively more valuable to more risk-averse buyers, which makes them more aggressive, reinforcing the higher surplus extraction exhibited by equity.

Informal auctions are another type of security-bid auction and are used extensively in takeover operations. In 2022 alone, the value of mergers and acquisitions amounted to $4.1 trillion worldwide, and many of these operations were conducted through auctions. This type of auction is arguably more complex than its formal counterparts because buyers can initiate the auction and can freely choose which securities they bid with, forcing the seller to form beliefs about buyers' types and leading to several adverse selection intricacies (Hansen, 1987; Fishman, 1989; Eckbo et al., 1990). DKS shows that in the signaling equilibrium of this game under risk-neutral buyers, all buyers must choose the flatter security (which in our case is debt) to express their bids, while Fioriti and Hernandez-Chanto (2021) claims that when buyers are risk-averse, they may separate themselves in securities according to their risk preferences.

The types of auctions that we study here are sufficiently rich to study the tradeoffs entailed by each security design in formats whose equilibria vary in their cognitive demands. For instance, the second-price auctions (under both securities) have an equilibrium in dominant strategies, whereas the first-price auctions (under both securities) have a Bayesian equilibrium. The informal auction involves multiple steps and may feature equilibria in which buyers pool within a particular security or separate based on risk preferences, as discussed above.

Experimental design We construct the simplest environment in which the surplus extraction and insurance provided by each security design can be compared. Subjects act as buyers bidding for the rights to implement a risky project. All subjects are given an endowment, but the winner of the auction must invest that endowment in the project. Essentially, the winner of the auction surrenders her endowment and is given back a lottery whose payoffs depend on the "price" at which she got the project. In the case of the first-price auction, the price is equal to the winner's security-bid, whereas in the second-price auction, it is equal to the second-highest security-bid. The project then generates either high or low revenue. Buyers receive signals indicating the likelihood that the project generates high revenue. Thus, these signals determine their (private) valuations. The endowment, the project's revenue, and all payments are made with experimental points.

As discussed above, we implement five treatments: (1) first-price debt auctions, (2) first-price equity auctions, (3) second-price debt auctions, (4) second-price equity auctions, and (5) informal auctions. In all treatments, two subjects are randomly matched in each round to take on the role of buyers. In informal auctions, a third subject takes on the role of the seller to choose the winner of each auction after observing buyers' submitted bids. This is the minimal competition environment that we need to evaluate the performance of securities across formats. We use a between-subjects design, with one treatment per experimental session.

In all treatments, subjects play 20 rounds of auctions. In each auction, the buyers receive their private signals (drawn from a uniform distribution on the unit interval) and make bids. This is followed either by the rules determining the winner (for formal auctions) or a third subject choosing the winning bid (for informal auctions). At the end of each round, all subjects involved in the auction are informed of who won and all bids that were made.

After completing the auctions, all subjects participate in 10 rounds of the Andreoni and Harbaugh (2009) risk elicitation task. This allows us to connect bidding behavior to risk attitudes, which the theoretical literature identifies as an important factor in buyers' valuations for these risky projects. Subjects complete the experiment with a short survey.

Findings We obtain mixed results relative to the extant theoretical predictions about revenue and surplus generated by these auctions. Contrary to most theoretical predictions, debt auctions (in both formats) generate the highest revenue. They are followed by first-price equity auctions. Second-price equity auctions and informal auctions generate the lowest revenue. All auctions exhibit some inefficient allocations, but the differences in efficiency between treatments are small relative to the overall surplus.

We find significant overbidding relative to the risk-neutral Nash equilibrium (RNNE) in debt auctions. This is part of what leads to higher revenue for debt auctions than equity auctions. However, the rate at which subjects make *dominated* bids is not differentially higher for the debt treatments: the overbidding that is more prevalent in the debt treatments is consistent with risk-loving preferences (although we stress that we do not believe that risk preferences explain the differences between treatments). Overbidding decreases with experience and is correlated with some subject characteristics such as quiz score and confidence, but it is not correlated with their choices in the Andreoni-Harbaugh task.

In our informal auctions treatment, we again find patterns that are only consistent with some theoretical results. Subjects make their bids using equity more often than with debt, which contradicts the theoretical prediction under risk neutrality that all bids should be made using debt. Average bids are close to the equilibrium bids of the first-price formal auctions for the respective securities. The subjects who act as sellers overwhelmingly choose the better bid when one bid dominates the other. We find these results remarkable because the cognitive demands of the informal auction are arguably higher than those of formal auctions.

Relevance of the experimental approach Despite the fact that security-bid auctions are both common and economically important, empirical evidence about these auctions (discussed further in Section 2) is limited. One of this paper's primary contributions is to compare auction formats and security designs without the need for structural assumptions or identification arguments. Thus, we believe that this is an important building block that complements the extensive theoretical work and the nascent empirical literature.

Previous work has shown that, more often than not, experienced professionals perform similarly to standard laboratory subjects (Fréchette, 2011). For instance, Dyer et al. (1989) shows that in common value auctions, undergraduate experience with no laboratory experience bid similarly to construction executives with years of bidding experience. Furthermore, the results of laboratory experiments have guided the design of complex and valuable auctions such as the FCC's spectrum auctions (Goeree and Holt, 2010; Roth, 2016). While the subjects in our experiment are potentially less sophisticated than firms making bids, the environment is much simpler than similar auctions from the real world.

2 Related Literature

There is a growing theoretical literature studying auctions with contingent payments. Early work by Hansen (1985) showed that a second-price equity auction yields greater expected revenue for the seller than cash auctions. This was extended by Riley (1988) and Rhodes-Kropf and Viswanathan (2000) to auctions that combine cash and equity. DKS extends these analyses further to general securities and introduces the notion of steepness as a partial order to compare securities. They show that steeper securities yield the seller a greater expected revenue because the winner's payment is tied more tightly to her true project's valuation. Fioriti and Hernandez-Chanto (2021) shows that steeper securities also provide higher insurance to risk-averse buyers, making them more aggressive. This reinforces the sellers' incentives to choose steeper securities. Nonetheless, other works find the opposite effect of steeper securities on expected revenue under richer environments such as adverse selection (Che and Kim, 2010; Liu and Bernhardt, 2019), moral hazard (Kogan and Morgan, 2010), competing sellers (Gorbenko and Malenko, 2011), and negative externalities (Hernandez-Chanto and Fioriti, 2019).

Although the properties of securities auctions have been extensively explored, empirical evidence examining these properties is limited due to the difficulty of testing these results in the field. The notable exception is the empirical analysis of oil auctions—e.g. Kong (2021), Bhattacharya et al. (2022), and Kong et al. (2022). The experimental approach complements this literature because it allows us to observe individuals' choices in controlled environments. Thus, we can directly observe the effects of counterfactual selling mechanisms on buyers' and sellers' behavior without concerns about complementarities between projects, common values, repeated game incentives, or other omitted variables.

The only other experimental analyses of auctions with securities that we are aware of are Kogan and Morgan (2010) and Bajoori et al. (2022), which is contemporaneous to our work.

Kogan and Morgan (2010) analyzes a situation where two entrepreneurs must compete for a package of funds provided by an investor by bidding in either equity or debt. The salient characteristic is that once the project is allocated to the winner, she can exercise effort to increase the value of the project. The returns to effort are fixed and only affect profits if the project is successful. Thus, this is a setting with *moral hazard*, and the authors' interest is to analyze the *extraction-incentives* tradeoff implicitly entailed in the equity-debt choice: equity is more extractive but induces agents to exert less effort, whereas debt does the opposite. To do so, they conduct an ascending English auction and allow subjects to choose whether they pay a cost to "exert effort." Unlike Kogan and Morgan (2010), we abstract from moral hazard considerations but consider both first and second-price auctions, along with informal auctions. Using sealed bid auctions allows us to observe all bids and to make comparisons across auction formats.[2]

Bajoori et al. (2022) studies first- and second-price auctions using cash and equity with a sample of online subjects from Prolific. Signals take one of four values, and subjects make bids for a single repetition of the game using the strategy method. The results show that first-price equity auctions raise the most revenue, but both cash auction formats raise more revenue than second-price equities auctions. This paper differs from Bajoori et al. (2022) in several ways. First, we consider an informal mechanism in addition to formal auctions. Second, we compare auctions using two different types of securities, rather than comparing cash auctions to securities auctions. Third, we use a richer signal space but only allow for revenue to take one of two values. Fourth, we conduct our experiment in the laboratory and allow subjects to gain experience with their treatment format and security. Our results are substantively different from those of Bajoori et al. (2022). While they find that equity auctions outperform cash auctions in terms of revenue (the steeper security dominates), we find that debt auctions outperform cash auctions (the flatter security dominates). Furthermore, in our data, the most prevalent feature of the data is *overbidding* (consistent with

[2] Although second-price auctions are strategically equivalent to English auctions, they are not obviously strategy-proof (Li, 2017). Thus, the more complex format plus the security design may increase the cognitive demands of playing the game on buyers.

previous experimental work with cash auctions), while *underbidding* is more prevalent in Bajoori et al. (2022).

In addition to contributing to the nascent literature of experimental security-bid auctions, we also add to the discussion about auctions of objects with contingent valuations, as in Ngangoué and Schotter (2023). They consider both common value auctions (CV) and common probability (CP) auctions. In CV auctions, the potential value of the object is uncertain, while in CP auctions, the probability of achieving known values is uncertain. The authors compare the auctions experimentally, finding overbidding in CV auctions but bidding close to the RNNE in CP auctions. As in CP auctions, the subjects in our security-bid auctions receive signals about the likelihood of high revenue, but this likelihood is independent across subjects (i.e. this is an IPV setting)[3]. Instead, we add to this literature by allowing for payments that are contingent on the payoff of the asset.

We revisit the literature on overbidding in cash auctions in Section 6.1 to determine whether the postulated theories in those models can explain the behavior exhibited by subjects across treatments in our experiments. We consider variations to buyers' preferences such as risk aversion, spiteful bidding, joy of winning, regret, and probability weighting. While bidding behavior appears to be noisy, we discuss why quantal response equilibrium does not match the patterns we see in our data. We discuss other alternative equilibrium concepts such as cursed equilibrium, impulse balance equilibrium, and level-k reasoning. Finally, we examine explanations that involve misperceptions on the part of subjects.

[3]One justification for this valuation structure provided by DKS is that bidders might have different managerial abilities, which cause the project to generate different stochastic revenues depending on the identity of the winning bidder

3 Theoretical predictions and hypotheses

In this section, we discuss the theoretical results that are relevant to our experimental design. We present the simplest possible environment that captures the main features of security-bid auctions in a transparent way.

There is a risk-neutral seller interested in allocating an indivisible project between two buyers. The seller uses either a formal first- or second-price auction or an informal auction. The seller announces the chosen mechanism and commits to it.

Any buyer needs to make a non-contractible investment of $\kappa = 2000$ to implement the project. This investment can be thought of as the opportunity cost of the funds diverted from buyers' portfolios and is common knowledge to all buyers. If buyer i acquires the project and makes the required investment, the project yields a stochastic and contractible revenue of $Z_i \in \mathcal{Z} \triangleq \{z_L, z_H\}$. Here, $z_L = 2000$ refers to the revenue that the project yields in the low state of the world, and $z_H = 6000$ refers to the revenue in the high state. The project is useless if it is undertaken by the seller, but because the lowest possible revenue is equal to the implementation cost, it is valuable for all buyers with a strictly positive likelihood of receiving the high revenue.

Each buyer i receives a private signal $p_i \in [0, 1]$ that corresponds to the probability of being in the high state. Hence, the distribution of Z_i conditional on the buyer's signal is Bernoulli with parameter p_i. Signals are drawn independently from a uniform distribution, which is common knowledge.

Securities Bids are expressed by derivative securities in which the underlying asset is the project's revenue Z. A security is a function that maps $\mathcal{Z}$ to payments to the seller. We focus on two types of securities, presented below.

- Debt: When the buyer wins the auction at a "price" of d, she retains all revenue above d. That is, the payment to the seller for any revenue z is $D(z, d) = \min\{z, d\}$.

- Equity: When the buyer wins the auction at a "price" of e, she retains a proportion $1-e$ of the revenue. That is, the payment to the seller for any revenue z is $E(z, e) = ez$.

A graphical representation of these securities and how they map revenue to payments can be found in Figure 1.

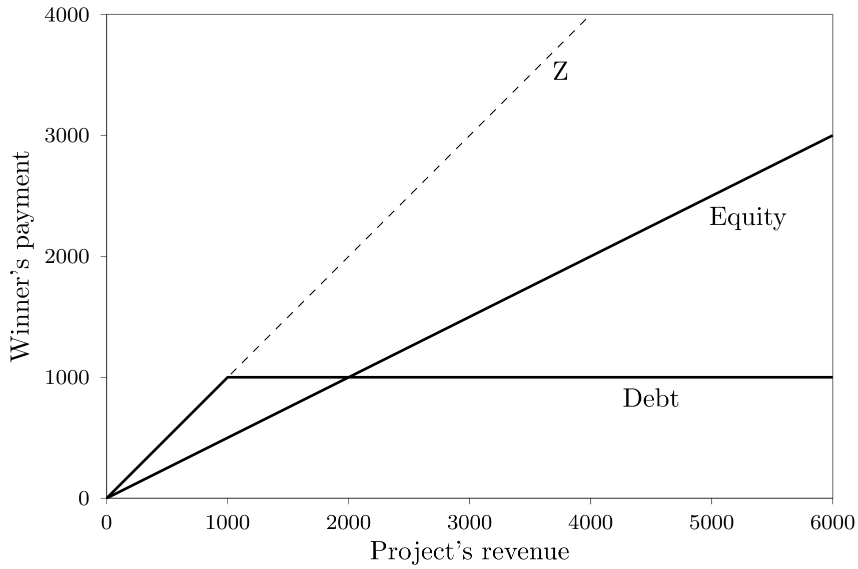


Figure 1: Example payments from the winner to the seller for debt and equity.

Debt and equity auctions share characteristics with many types of auctions that are used in practice. For instance, in the US, the local governments of Arizona, Louisiana, New Mexico, and Texas, among others, use fixed-equity auctions to allocate the rights to exploit their fields. In these auctions, the seller fixes an equity rate and buyers compete for the rights of the field via a cash auction. Although these states share the selling mechanism, the equity rates display variation: in Texas, the rate is fixed at 25%, whereas in Colorado and New Mexico, it varies between 18.75% and 20%, and in Louisiana, it varies between 20% and 25%.[4] Meanwhile, many sellers opt to use "stapled finance" in takeover operations. Stapled finance refers to a loan, in terms of debt or other securities, "stapled" onto an offering by the investment bank advising the seller in a takeover operation. The figure is available to whoever wins, but the winner is under no obligation to accept the loan offer. Stapled finance has been increasingly used in the US and Europe because, as shown by the empirical evidence, it increases the competition and the final price paid to the seller (Povel and Singh, 2010).

Selling mechanisms We analyze selling mechanisms based both on formal and informal auctions. In formal auctions, the auction format (first- or second-price) and security design (debt or equity) are predetermined. Hence, buyers are unable to make bids in any security other than the one that the rules specify.

Conversely, in informal auctions the buyer is not restricted to making bids exclusively from a particular ordered set. Instead, they are allowed to choose whether to bid with debt or with equity, but not from both. In that sense, as DKS points out, the "security design is in the hands of the buyers" rather than in the seller's. Once buyers submit their bids, the seller updates his beliefs over buyers' signals and chooses the most attractive bid ex-post. Hence, in this environment, the choices of securities by buyers play the additional role of serving as a signaling device about their types. As such, informal auctions can be thought as first-price scoring auctions, in which the score of each bid is determined by the seller's beliefs and buyers pay their security bid.

[4]Recently, the state of Louisiana has implemented auctions in which firms can bid in cash and equity instead of fixing the equity rate (see Kong et al., 2022).

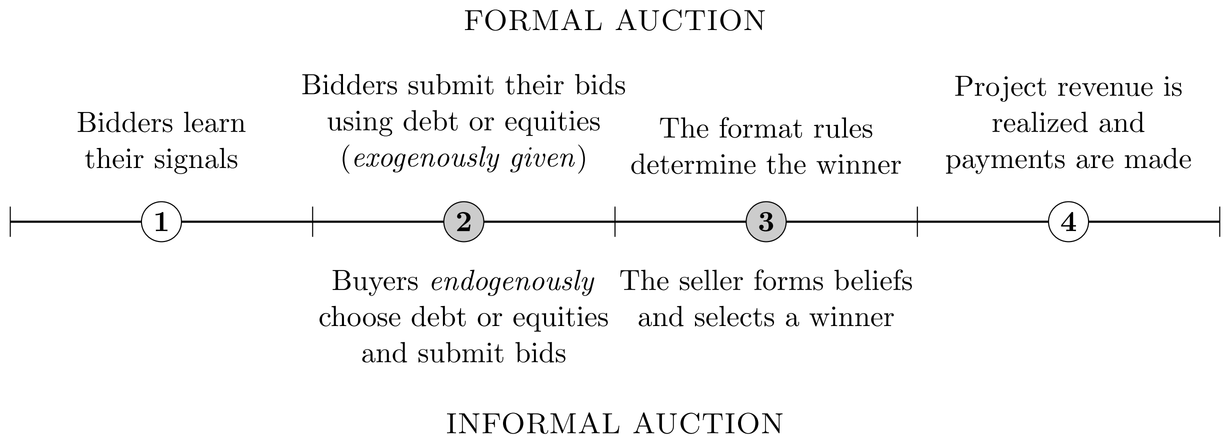


Figure 2: Timing for formal and informal auctions.

Timing Figure 2 depicts the timeline in formal and informal auctions. In formal auctions, buyers learn their signals about the stochastic revenue of the project. Then, they submit their bids from the ordered set of securities used by the seller to run the auction. Using such bids, the seller determines the winner following the rules of the auction's format (e.g., first- or second-price). Finally, payments are made according to the security-bid submitted and payoffs are realized. In informal auctions, the fundamental difference comes from steps 2 and 3. In step 2, buyers *freely* choose a security from the available menu of securities (debt or equity, but not combination of them), and in step 3 the seller chooses the best bid according to his beliefs about buyers' signals.

3.1 Behavior in Second-Price Auctions

In a second-price auction, the winner is the buyer who submits the highest bid, and the final price paid corresponds to the second-highest bid.

As in second-price auctions using cash, buyers have a weakly dominant strategy to submit a bid such that they are indifferent between losing the auction and winning at a price equal to their bid. In fact, DKS shows that the unique symmetric equilibrium is for buyers to bid in this way. In the case of equity, this implies that the equilibrium bidding function $e_2^*(p)$ satisfies

$$0 = (1 - e_2^*(p))[pz_H + (1-p)z_L] - \kappa. \tag{1}$$

The left-hand side of equation (1) reflects that the buyer receives payoffs of zero conditional on losing the auction, and the right-hand side gives the expected payoffs of the buyer if they won at a price of $e_2^*(p)$. A similar computation can be carried out for second-price debt auctions. This leads us to our first prediction for the experimental data.

Hypothesis 1. *In second-price auctions using debt, buyers will bid according to*

$$d_2^*(p) = \begin{cases} 4000p \ \textit{if} \ p \leqslant \frac{1}{2} \\ 6000 - \frac{2000}{p} \ \textit{otherwise} \end{cases},$$

while in second-price auctions using equity, buyers will bid according to

$$e_2^*(p) = \frac{2p}{2p+1}.$$

3.2 Behavior in First-Price Auctions

In the first-price auction, the buyer that submits the highest security-bid is selected as the winner and pays her bid. We focus on symmetric and monotone equilibria of these games. For instance, given and equilibrium bidding function of $e_1^*(p)$ in the first-price equity auction, the buyer's maximization problem can be stated as

$$\max_{e \in [0,1]} F(e_1^{*-1}(e))[(1-e)(pz_H + (1-p)z_L) - \kappa]. \tag{2}$$

The first term in (2) is the probability of winning the auction with a bid of e, while the second term corresponds to the buyer's expected payoff conditional on winning. Equilibrium requires that the solution of the problem in (2) is $e_1^*(p)$, implying that the equilibrium bids will be the solution to a differential equation. A similar exercise can be carried out for first-price debt auctions. This gives us predictions for bidding in first-price auctions for both securities.[5]

Hypothesis 2. *In first-price auctions using debt, buyers will bid according to*

$$d_1^*(p) = 2000p,$$

while in first-price auctions using equity, buyers will bid according to

$$e_1^*(p) = \frac{p - 0.5\ln(2p+1)}{p}.$$

3.3 Behavior in Informal Auctions

In informal auctions, buyers are not required to make bids from a specific ordered set. Thus, sellers are forced to form beliefs about the revenue generated by each bid to select the winner. Buyers anticipate this and understand the selection of security has not only an effect regarding the extraction and insurance, but also plays the additional role of being a signaling channel, leading them to engage in a signaling game.

To analyze informal auctions, we focus on symmetric pure strategy equilibria in which buyers can choose a security-bid from either debt or equity. Thus, a buyer's strategy maps their signal to a choice of an ordered set of securities and a bid within that set. Given a

[5]We confirm that these bidding strategies form an equilibrium in Online Appendix A.1.

profile of bids, the seller forms posterior beliefs about the signal that the buyer received, following the Bayes' rule whenever possible, and selects a winner. In any equilibrium of this game, the seller must be selecting the bid with the highest expected payoffs given his beliefs, and the buyers must choose securities and make bids that maximize their payoffs given all other strategies.

DKS argues that the seller's beliefs will depend crucially on the type of security that the buyer chooses. Specifically, in our setting, buyers with higher signals will have a relatively stronger preference for debt over equity, because equity leads to higher payments in the high state.[6] Thus, if the seller observes that one buyer deviates to debt, such a deviation must come from a high-signal buyer. Nonetheless, a low-signal buyer can anticipate this and mimic the deviation of the high-signal buyer. Under risk neutrality, this reasoning unravels, resulting in both types of buyer choosing debt. Because the seller will choose the highest bid in equilibrium and the winning buyer must pay their bid, the equilibrium outcome is equivalent to that of a first-price debt auction.

Hypothesis 3. *In informal auctions under risk neutrality, buyers will choose debt and the equilibrium will be equivalent to that of a first-price debt auction.*

Fioriti and Hernandez-Chanto (2021), on the other hand, argues that when buyers have heterogeneous risk aversion (parameterized by the different concavities of their utility functions), the auctions will not unravel in this way. This result stems from the fact that if a high-signal buyer is also highly risk-averse, then she would not necessarily deviate to choose a flatter security because, although it extracts less surplus ex-post, it provides lower insurance. Hence, a sufficiently risk-averse buyer would prefer to choose a steeper security.

[6] This is related to the fact that equity is "steeper" than debt.

Hypothesis 4. *In informal auctions, more risk-averse buyers will make bids using equity while less risk-averse buyers will make bids using debt.*

3.4 Revenue and Efficiency

A core focus of the literature on auctions with securities has been the revenue comparisons between different securities and selling mechanisms. Early work by Hansen (1985), Riley (1988), and Rhodes-Kropf and Viswanathan (2000) showed that auctions using equity could be superior to standard cash-bid auctions. This result was later generalized by DKS to standard securities that satisfy two-sided limited liability. Because we can compute explicit equilibria for our parametric model, we can generate clear predictions for the revenue rankings of the security designs and auction formats.[7] The hypotheses that we present are about *interim* revenue and surplus, meaning that they are about expected revenue and surplus conditional on the allocation of the project (but not conditional on the realization of the project's revenue).

Hypothesis 5. *First- and second-price equity auctions generate the highest revenue. First-price debt auctions and informal auctions generate the lowest revenue. Second-price debt auctions generate intermediate revenue.*

It is important to note that while the parametric nature of our model allows us to give point predictions for revenue, the *ranking* implied by these predictions is much more general. This ranking follows the results of DKS, which characterizes securities in terms of what they call steepness. A security is steeper than another if the seller's expected payment has a

[7]With the parametric assumptions we have made, the predicted revenues are approximately: 1722.9 (for first- and second-price equity), 1363.7 (for second-price debt), and 1333.3 (for first-price debt and informal auctions). The computation of these values can be found in Online Appendix A.2.

"greater slope" under the steeper security, starting at the signal level at which both securities yield the same expected payment. From Figure 1, it can be seen that equity is steeper than debt. DKS shows that under fairly general conditions, steeper securities generate higher revenue.[8]

The theoretical results from the securities auction literature also provide strong predictions about the relative efficiency of the auction formats. In the equilibria described above, bidding strategies are increasing in the buyers' private signals. Thus, the project is always assigned to the buyer with the highest chance of generating the high revenue.

Hypothesis 6. *All auctions are efficient.*

The equilibria we describe above rely on the buyers' risk neutrality. However, because the project is inherently risky, risk preferences are expected to play an important role in bidding behavior. The role of risk preferences in first-price auctions is complex, but the dominant-strategy nature of second-price auctions allows us to generate some predictions in this setting. When buyers are risk-averse in second-price auctions, they shave their bids relative to what they would have bid had they been risk neutral. This behavior is more pronounced when buyers are more risk-averse. Hence, with heterogeneous risk aversion, a more risk-averse buyer with a high signal could bid lower than a less risk-averse buyer with a lower signal. In this case, the formal auction mechanisms studied here are not necessarily interim efficient. Fioriti and Hernandez-Chanto (2021) show that, when buyers in second-

[8]Another notable feature of these auctions is that the celebrated Revenue Equivalence Theorem, introduced by Myerson (1981) for cash auctions, holds for auctions under equity but not under debt. The reason is that the family of equity is closed under convex combinations, and, hence, any convex combination of equity securities generates an equity security. This implies that the problem buyers face in the second-price auction, where they must choose a random bid, can be expressed as choosing a deterministic bid from the equity convex hull—which is, precisely, constituted of equity. Hence, both problems are isomorphic. Meanwhile, the family of debt is sub-convex; that is, a convex combination of debt securities generates a security that is steeper than debt. Hence, in this case, buyers are implicitly choosing bids from an instrument that is steeper than debt in the second-price auction.

price auctions are risk-averse, equity provides buyers with more insurance than debt. This is because they smooth payoffs across realizations, asking for lower payments in the low state and for higher payments under the high state. The insurance effect is more valuable for more risk-averse buyers, making them relatively more aggressive. The increase in aggressiveness makes the handicap of risk-averse levels on bids be less severe, increasing the allocative efficiency of the auction.

Hypothesis 7. *A second-price auction under equity is weakly more allocatively efficient than a second-price auction under debt.*

4 Experimental Design

The experiment consisted of 16 sessions conducted at the University of Queensland Behavioural Economics Science Cluster (BESC) between August 2021 and April 2022. Subjects were recruited using Sona Systems, and a total of 215 subjects participated. Demographic summary statistics can be found in Online Appendix Table 8. No subject appeared in more than one session. The experiments were completed in-person through computer terminals, and all experiments were coded using oTree (Chen et al., 2016). Screenshots for all parts of the experiment and for all treatments can be found in Online Appendix E.

The experiment consisted of five different treatments, with each subject seeing exactly one treatment (i.e. this was a between-subject design). As discussed above, the treatments were (1) first-price debt auctions, (2) first-price equity auctions, (3) second-price debt auctions,

(4) second-price equity auctions, and (5) informal auctions.[9,10] Two subjects acted as buyers in each formal auction. In the informal auctions, two subjects acted as buyers, one subject acted as the seller, and roles were fixed across rounds.

All sessions had the same structure. Subjects were first brought into a lab and directed to their terminal. They were given the opportunity to read a participant information sheet and to sign a consent form. Subjects were presented with instructions, including auction instructions and examples that were specific to their treatment, then took a quiz. They then participated in 20 rounds of auctions. After the auctions, subjects were read the instructions for a risk elicitation task and then completed 10 rounds of that task. After all subjects had completed all tasks, subjects completed a short survey, payments were made, and subjects left the laboratory.

Each subject participated in 20 rounds of auctions. They were randomly assigned a new partner in each round. On each bidding page, subjects were informed of the likelihood that their project would have high revenue. Furthermore, on all bidding pages, subjects were given the same interactive feature that they were given on the examples page, allowing them to easily identify the consequences of their bid.

In the formal auctions, subjects then needed to type in their bid (an integer from 0 to 6000 points in the debt auctions or an integer from 0 to 100 percent in equity auctions). An example bidding page can be found in Figure 3. After both players in a group made

[9]While subjects have been shown to perform better in ascending auctions, we chose to use the second-price format for two reasons. First, using a second-price auction allows for more direct comparison to first-price auctions, which also use sealed bids. Second, an ascending auction makes it impossible to observe the highest bid in the auction. This limits the number of bids observed per auction and complicates inference about bidding functions.

[10]The number of subjects participating in each of these treatments was 38, 40, 40, 40, and 57 respectively. Each formal auction had three sessions, while there were four sessions of the informal auction. Sessions in the formal treatments varied in size from 10 to 16 subjects. Sessions in the informal treatment varied in size from 9 to 21 subjects.

their bid, subjects were shown the results of the auction. Winners were told the other player's bid and their likelihood of receiving each potential outcome, but the realization of the outcome was not revealed to them.[11] Losers were told the other player's bid, the payoffs they would receive, and the potential payoffs of the winner. However, the loser was not told the likelihood that the winner would receive the high revenue (i.e. the winner's private valuation) or the realization of the revenue. An example of the results page for an auction winner can be found in Figure 4.

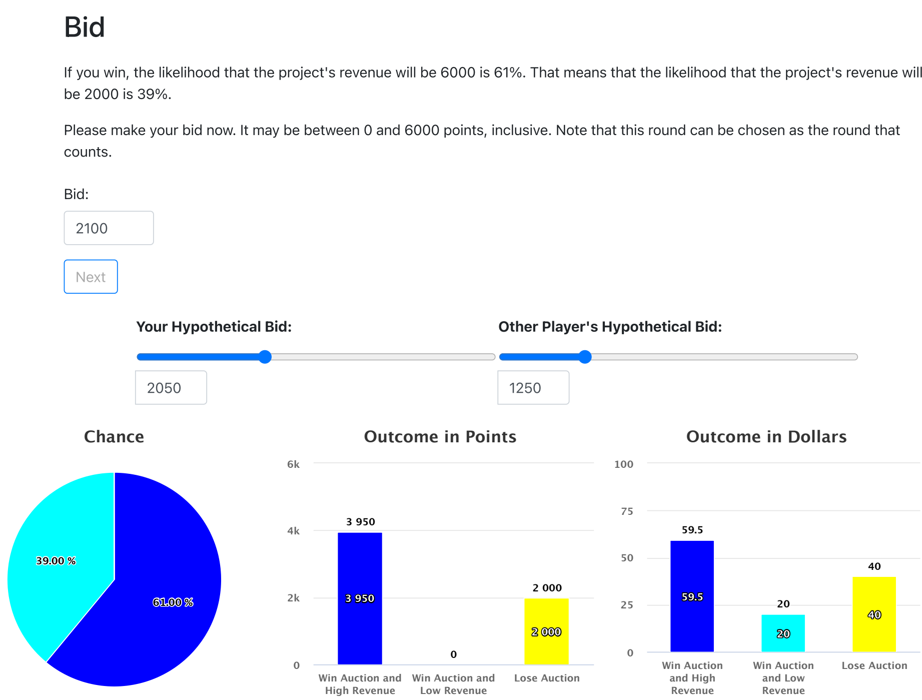


Figure 3: Bidding page for a first-price debt auction

[11] Theoretically speaking, whether or not the realization of the project's outcome is revealed should not have any effect on subjects' subsequent behavior, since it cannot reveal anything about the other player's signal because the probability of the project having high revenue was different for each individual. Thus, this additional information should not affect the buyer's risk preferences for subsequent lotteries because only one round is paid at random. However, as is common in most experiments involving decision making under risk, the lottery outcome is not realized until the end of the experiment.

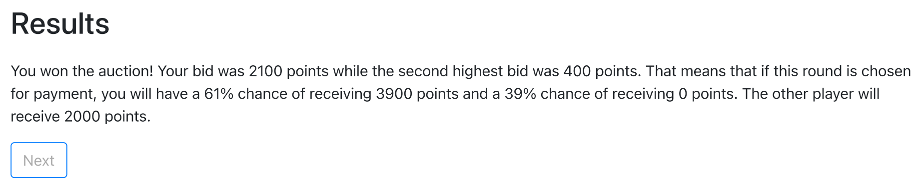


Figure 4: Results page after winning a first-price debt auction

In the informal auctions, buyers both chose their security and made their bid on the same page. Once both buyers made their bid, the seller was informed of the two bids that were made and was given a graphical display representing the potential payoffs that would arise from each bid. The seller then selected which buyer is the winner. The bidding page and seller's choice page for informal auctions can be found in Figures 5 and 6, respectively. As in the formal auctions, both buyers are informed of the bids that were made and who won. The seller is reminded of who they selected to win the auction, the payoffs they could receive as a result of the auction, and the fact that the probability of receiving the high payoff is unknown to them.

After completing the auctions, all subjects participated in 10 rounds of an individual choice task. The task, first developed in Andreoni and Harbaugh (2009), is a risk elicitation task that allows for the evaluation of subjects' attitudes towards both monetary prizes and probabilities of receiving those prizes (Breig and Feldman, 2024). In each task, subjects are asked to trade off between the size of a price and the likelihood of receiving that price using a linear budget. Subjects faced five unique budgets in a random order and then faced the same five budgets in a newly randomized order. The five budgets that subjects faced had maximum prizes of 8000, 10,000, 12,000, 16,000, and 20,000 points, with corresponding maximum probabilities of 0.8, 1, 0.6, 0.4, and 0.5. A graphed version of these budgets can

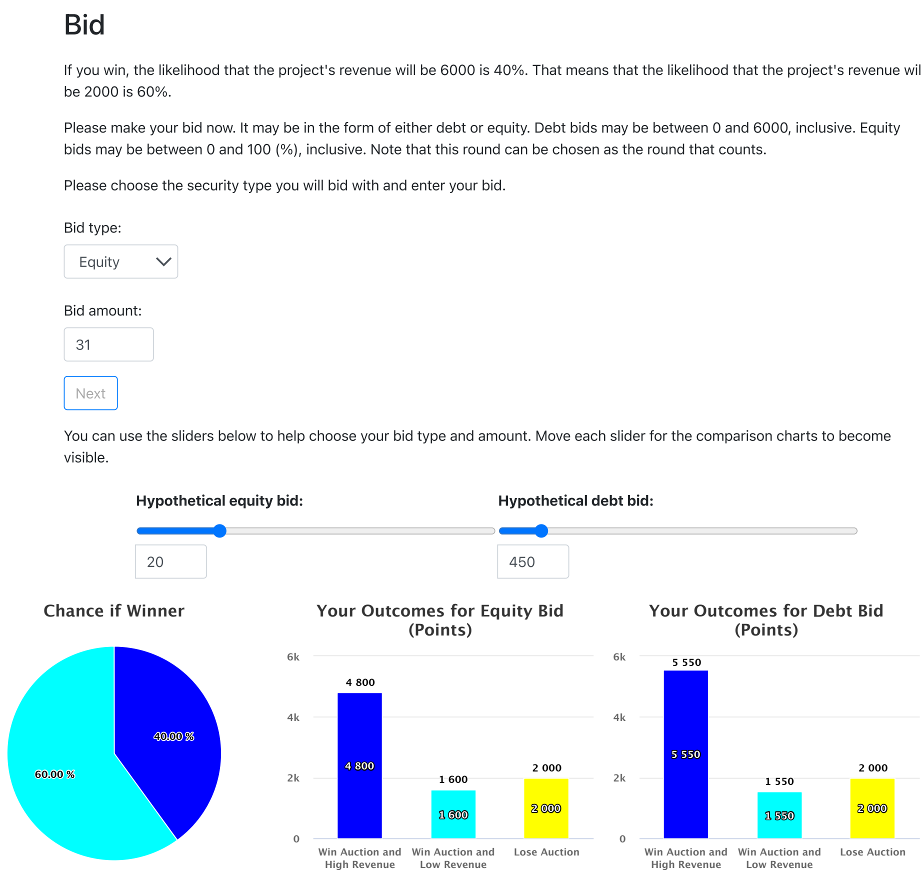


Figure 5: Bidding page for an informal auction

be found in Online Appendix Figure 20.[12]

Upon the completion of all tasks, the computer randomly selected a single round for each subject from either the auctions or the Andreoni-Harbaugh tasks to be the one that counts. The subject was told which round was selected as well as the potential outcomes and associated probabilities. After being presented with this information, subjects were informed of the results of any randomization and their total payments. They then completed

[12]In addition to measuring risk preferences directly, these 10 tasks allow for a rich set of revealed preference measures. While they are not the focus of our analysis, we discuss these measurements and how they are related to behavior in the experiment in Online Appendix B.

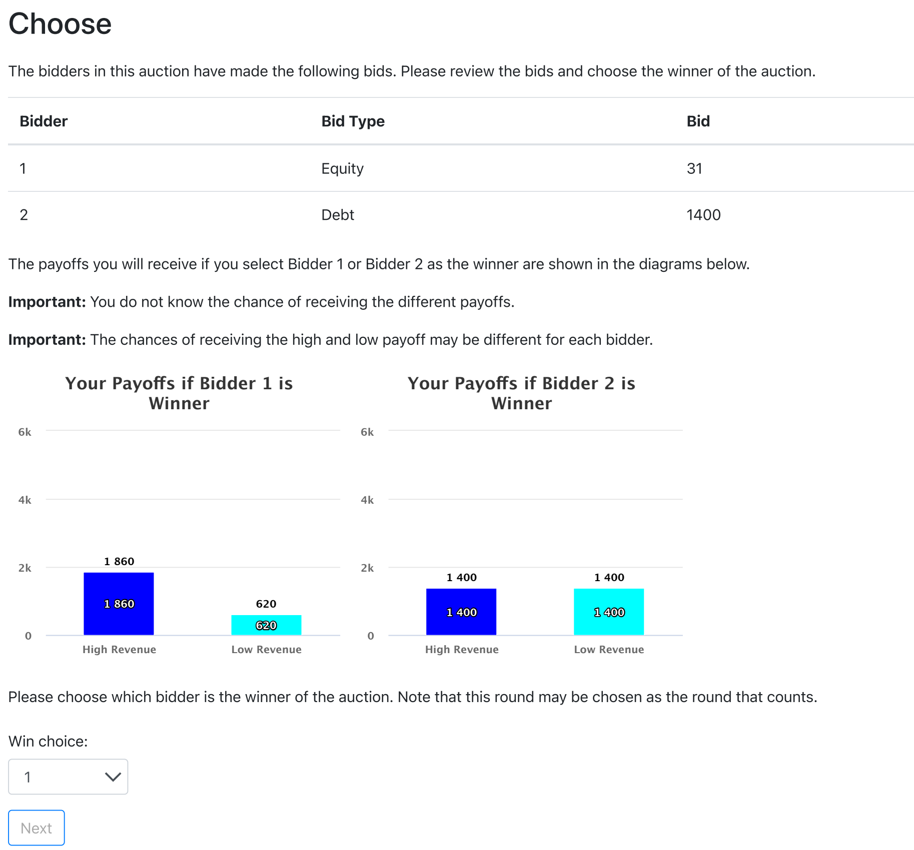


Figure 6: Seller's choice page for an informal auction

a survey involving demographic questions, experiment feedback, and a cognitive reflection test (Frederick, 2005).

In addition to any earnings from the round selected for payment, all subjects were paid a \$20 completion fee. Sessions lasted one and a half to two hours. Payments ranged from \$22 to \$110, and the average total payment was \$48.47.

We preregistered the experiment in the American Economic Association's RCT Registry (AEARCTR-0009157). This registration occurred after the informal auction treatment was completed, but before any sessions of the formal auction treatments. We completed power calculations based on the empirical outcomes from the informal auctions (details can be found in the pre-analysis plan published on the AEA RCT Registry).

5 Results

5.1 Revenue and Efficiency

In this section, we compare the results on revenue and efficiency obtained in the experimental auctions vis-à-vis the corresponding theoretical predictions. From a given auction, the revenue and efficiency measures are conditional on the winning buyer's signal; thus, they are computed from an interim perspective. Additionally, to compute the measure of efficiency we look at the *potential surplus*, i.e., the surplus produced in case the project were implemented by the highest-signal buyer. We then take the average of both measures across auctions within each treatment.

Before stating our results about the allocation of surplus formally, we summarize them graphically with Figure 7, which shows the predicted and realized average distribution of surplus across treatments. One can immediately see that there are large differences between treatments and that the differences do not necessarily reflect the theoretical predictions. With the exception of the second-price auction under equity, all mechanisms exhibit a higher expected revenue than their theoretical counterparts. Moreover, the differences in revenue are more pronounced in debt than in equity auctions. In fact, the greatest revenue excess is produced under the first-price debt treatment, whereas the lowest is obtained under informal auctions. All treatments display allocative inefficiency, computed as the difference between the actual and potential surplus in each auction. This feature, along with the results on revenue discussed above, implies that the buyer's surplus is lower than in theory for all

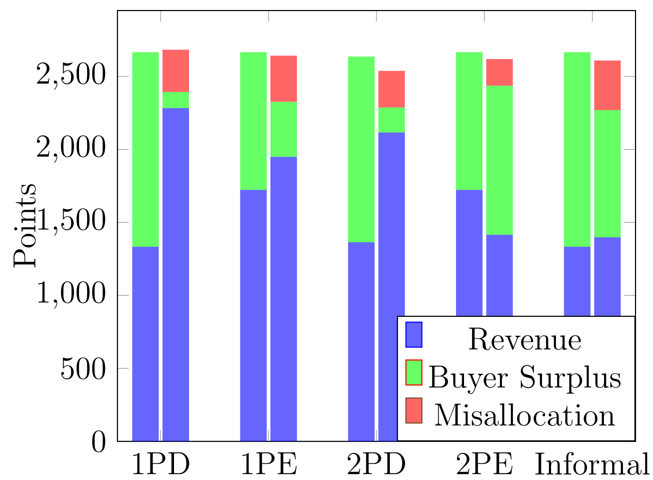


Figure 7: Comparison of average levels revenue and allocative efficiency in all selling mechanisms. For each treatment, theoretical predictions of risk-neutral Nash equilibria are on the left and empirical realizations are on the right.

mechanisms—with the exception of the second-price equity auction. Notably, this treatment is the one that generates the lowest efficiency loss.

Our first result is about the revenue raised within each treatment and relates to Hypothesis 5.

Result 1. *First- and second-price debt auctions raise the highest revenue. First-price equity auctions raise the second highest revenue. Second-price equity auctions and informal auctions raise the lowest revenue.*

The evidence for Result 1 is presented in Table 1, which presents the regression results using interim revenue as the dependent variable. The null hypothesis that all treatment coefficients are equal to zero is rejected at the 1% level for all specifications. In column (1), the independent variables are dummies representing the treatments, with the first-price debt treatment being the omitted treatment. This column shows that, in terms of raw averages, first-price debt auctions raised the highest revenue, followed by second-price debt, first-price equity, second-price equity, and informal auctions.

Columns (2) and (3) of Table 1 control for potential surplus and round, respectively.[13] When controlling for potential surplus, the difference between the revenue raised by first- and second-price debt gets smaller and becomes insignificant. The coefficient on round demonstrates that revenue decreases as subjects gain more experience, a point that will be explored further in Section 5.2.

Column (4) is our preferred specification and is our main evidence for Result 1.[14] The differences described in the result are statistically and economically significant. The implied gap between the revenue raised by first-price debt auctions and informal auctions is over 30% of the potential surplus generated by these auctions. Thus, we can conclusively reject Hypothesis 5.

Our next result is about the surplus generated by each treatment and relates to Hypotheses 6 and 7.

Result 2. *Second-price equity auctions generate the highest surplus. All other types of auctions generate surplus similar to each other.*

The evidence for Result 2 is presented in Table 2. The null hypothesis that all treatment coefficients are equal to zero is rejected at the 1% level for the specifications in columns (2)-(4), but not for the specification in column (1) (p-value 0.15). While the difference between second-price equity and the other treatments is not significant in raw averages, this difference

[13]Potential surplus is equivalent to the maximum of the two buyers' signals multiplied by 4000. Because this is a random variable drawn independently of the treatment, potential surplus should be uncorrelated with the treatment dummies. However, the fact that coefficients and patterns of significance change between columns (1) and (2) demonstrates that in our sample, potential surplus happens to be correlated with the treatments. This is shown explicitly in Online Appendix Table 20.

[14]The specification used in column (4) of Table 1 and column (4) of Table 2 were registered as the primary focus of our analysis in our pre-analysis plan. For completeness, we reproduce these regressions with only data from the second half of the experiment in Online Appendix Tables 10 and 11. The qualitative results are unchanged.

Table 1: Interim revenue

	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue
1PE	-333.9***	-307.6***	-307.7***	-307.7***
	(79.6)	(63.5)	(62.7)	(62.9)
2PD	-167.5**	-73.8	-74.2	-74.0
	(75.2)	(64.7)	(64.4)	(64.7)
2PE	-867.9***	-827.2***	-827.5***	-827.4***
	(77.5)	(66.0)	(65.6)	(65.8)
Informal	-884.5***	-837.2***	-837.4***	-837.3***
	(70.1)	(61.6)	(60.8)	(60.9)
Potential Surplus		0.65***	0.64***	0.64***
		(0.022)	(0.022)	(0.022)
Round			-15.8***	
			(3.61)	
Constant	2283.2***	552.4***	727.6***	856.2***
	(49.6)	(72.7)	(82.8)	(118.7)
Round FE	No	No	No	Yes
Observations	1960	1960	1960	1960

Notes: Linear regression with robust standard errors. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

does become significant at the 5% level when controlling for potential surplus. Column (3) shows that while surplus does increase on average with subjects gaining more experience, the increase is economically small and insignificant.

Our preferred specification is again presented in column (4). Here, we find that when controlling for potential surplus and round fixed effects, second-price equity auctions generate higher surplus than the other treatments, whose revenues are not in general distinguishable from each other. The fact that the auctions are not allocatively efficient contradicts Hypothesis 6. The efficiency ranking of second-price equity over second-price debt is consistent with Hypothesis 7, but the difference is only significant at the 10% level ($p = 0.056$).

Table 2: Surplus

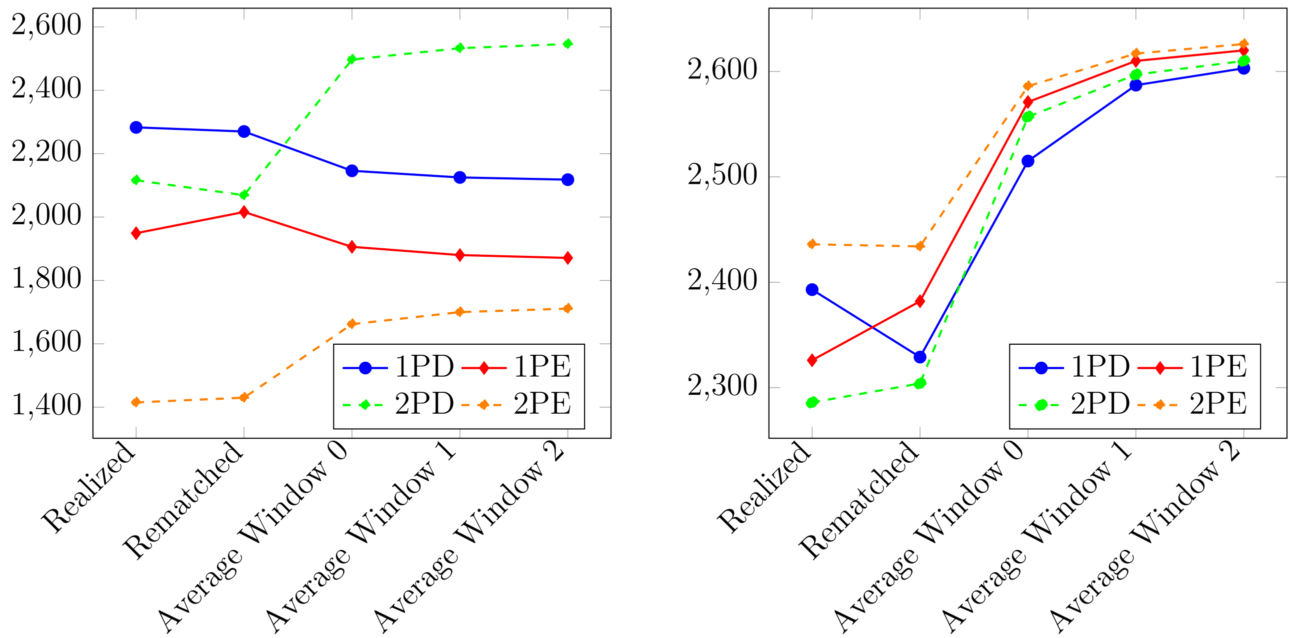
	(1) Surplus	(2) Surplus	(3) Surplus	(4) Surplus
1PE	-67.1	-27.4	-27.4	-27.5
	(78.7)	(44.9)	(44.8)	(44.6)
2PD	-106.7	34.6	34.7	34.5
	(78.6)	(40.8)	(40.9)	(40.7)
2PE	43.7	104.9***	105.0***	104.9***
	(76.8)	(39.8)	(39.8)	(39.8)
Informal	-123.5	-52.2	-52.1	-52.2
	(79.6)	(46.5)	(46.5)	(46.4)
Potential Surplus		0.97***	0.97***	0.97***
		(0.012)	(0.012)	(0.012)
Round			3.79	
			(2.37)	
Constant	2393.0***	-216.3***	-258.2***	-243.2***
	(55.6)	(40.5)	(48.3)	(72.8)
Round FE	No	No	No	Yes
Observations	1960	1960	1960	1960

Notes: Linear regression with robust standard errors. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Because the results for revenue and efficiency are in stark contrast to the theoretical predictions about them, we further explore the source of these results in Figure 8. The first (leftmost) point of the lines in panels (a) and (b) of the figure show the realized revenue and efficiency, respectively, for each of the treatments. The second point carries out a "rematching" procedure, in which each bid from a formal auction is put up against every other bid from that formal auction, then average revenue and surplus are computed. The next three points average all bids that received signals within particular windows and then compute average revenue and surplus based on these average bids.[15] In this way, we are able

[15]For instance, consider the bids for "Average Window 1" and consider the signal of 13%. To compute the average bid for a signal of 13%, we take the average of all bids within 1 unit from 13% (i.e. all bids from buyers who received signals of 12%, 13%, or 14%). We do this for *each* potential signal. We then create

to compute the counterfactual revenue and efficiency if subjects bid according to the average rather than noisy bids around that average.



(a) Revenue

(b) Surplus

Figure 8: Average surplus and revenue after rematching and averaging. "Realized" refers to the data from the experiment. "Rematched" gives average revenue and surplus after rematching every bid against every other bid from the same treatment. For the averaged numbers, bids are averaged within a particular window and then each average bid is matched against each other average bid from the same treatment. "Average Window 0" shows the results from averaging of all bids that received a particular signal, "Average Window 1" shows the results from averaging all bids within one percentage point of a signal, and "Average Window 2" shows the results from averaging all bids within two percentage points of a signal. Reducing decision noise (but retaining average bidding functions) leads to lower revenue in first-price auctions, higher revenue in second-price auctions, and higher surplus in all auctions.

artificial auctions in which the average bid for a signal of 0% is put up against the average bid for 1%, 2%, etc., and compute the overall average revenue and surplus from this exercise. Because no subjects received a signal of 37 in the second-price debt treatment, we replace the average window 0 with the average window 1 for that signal.

Result 3. *Averaging bids by signal increases the revenue of second-price auctions but decreases the revenue of first-price auctions.*

The evidence for Result 3 can be found in Panel (a) of figure 8. Computing revenue based on average bids significantly increases the revenue raised by second-price auctions and decreases the revenue raised by first-price auctions. In fact, the effect is strong enough that it overturns the ranking presented in Result 1, and instead leads to second-price debt auctions raising the maximal revenue. The fact that averaging in this way favors second-price auctions and disfavors first-price auctions is intuitive. Fixing average bids, adding noise to an auction with two buyers tends to increase the highest-order statistic and decrease the second-highest-order statistic. Thus, averaging bids by signal tends to decrease the realized price and revenue in first-price auctions while increasing the realized price and revenue in second-price auctions.

Result 4. *Misallocation is primarily due to noisy bidding rather than non-monotonic average bids.*

The previously discussed pattern of noisy bidding also has a significant affect on efficiency. When bids are noisy, sometimes buyers with lower signals make higher bids than those with higher signals. This decreases surplus because the project is being allocated to the buyer with a lower private valuation. When noise is decreased by averaging bids over a sufficiently wide window, the total surplus of all treatments is essentially the same and approaches the theoretically predicted surplus of 2667.

5.2 Bidding in Formal Auctions

In this section, we investigate the distinctive features in buyers' behavior that lead to the results in revenue and efficiency found in all formal selling mechanisms. Hypotheses 1 and 2 state the Nash equilibrium bidding strategies for these settings.

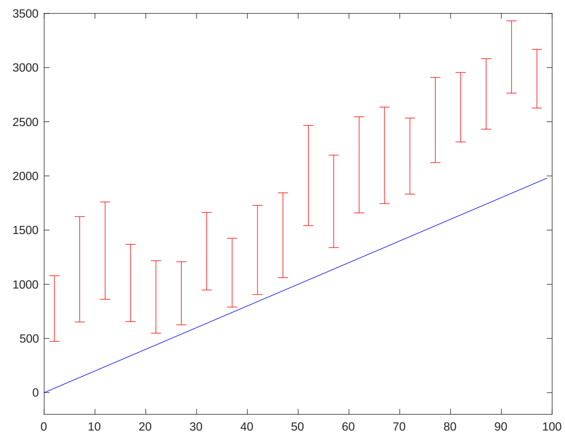
Result 5. *In formal auctions, subjects overbid on average for all signals in both first- and second-price debt auctions. Subjects overbid on average for extreme signals (both high and low) for both first- and second-price equity auctions.*

Figure 9 compares the theoretical Nash equilibrium bidding function under risk neutrality to bids from the experiment. Bids are averaged within windows of 5 signals (0-4, 5-9, etc.) and presented with 95% confidence intervals for the average. It is immediately apparent that in debt auctions there is substantial overbidding under both formats—the risk-neutral Nash equilibrium is outside of the confidence interval for the average bid for each of the ranges of signals. In equity auctions, there is similar overbidding for low and high signals, but average bids are either close to or below the Nash equilibrium for intermediate signals.[16][17] In follow-up work, Breig et al. (2023) shows that the patterns of overbidding observed in this paper's second-price treatments are replicated using a within-subject comparison of second-price equity- and debt-bid auctions. Thus, the differences between security designs are unlikely to

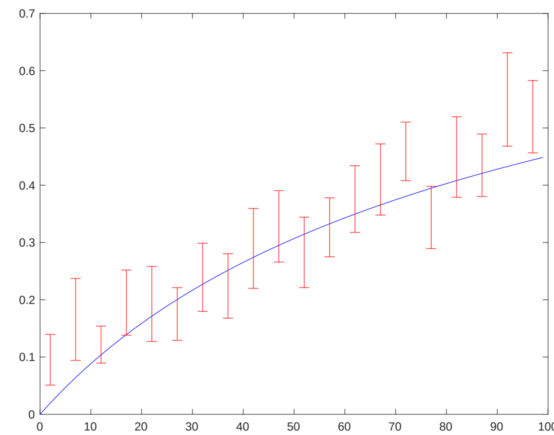
[16] Because the RNNE in both types of second-price auction involve weakly dominant strategies, the equilibrium strategy is also the empirical best response. We compare behavior in the first-price auctions to their respective empirical best responses in Appendix Figure 19. For the majority of signals in both settings, the empirical best response is below the RNNE bid.

[17] We further analyze how the level of the buyer's signal affects overbidding nonlinearly in Online Appendix Table 12, which shows regression results of the level of overbidding (bid minus equilibrium bid) on signal and signal squared with subject fixed effects. We find that, broadly speaking, overbidding is positive for low signals, decreases for intermediate signals, and increases again for high signals. This parabolic overbidding pattern in the second-price debt and equity auctions is consistent with the results in Fioriti and Hernandez-Chanto (2021) because buyers shave their bids relative to the equilibrium when the signals are close to 0.5—i.e. when the variance of the project's revenue is maximal.

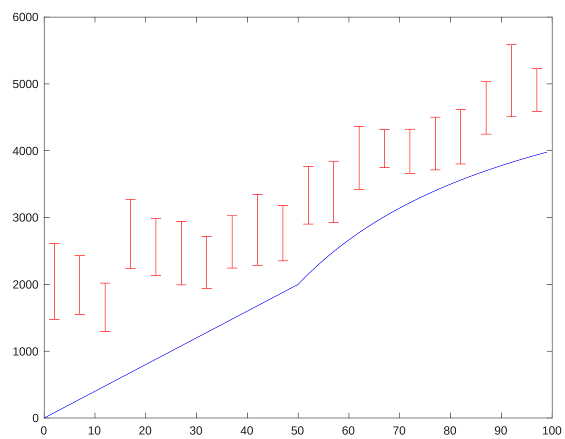
be the result of random variation or session-level effects. Hence, the security design is more important than the auction format for overbidding.



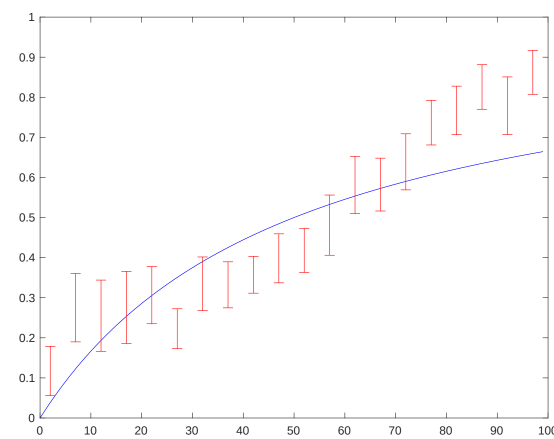
(a) First-price debt



(b) First-price equity



(c) Second-price debt



(d) Second-price equity

Figure 9: Average bids conditional on signal in formal auctions. Bids are averaged in windows of 5 units and presented with 95% confidence intervals. Equilibrium bidding functions are shown in blue.

Since overbidding is the main driver of the empirical revenue ranking obtained in the previous section, it is worth inspecting this overbidding more closely. Figure 10 classifies each bid into one of four categories. A bid is classified as "Dominated" if it could lead to a lottery that is first-order stochastically dominated by the buyer's outside option (this occurs when the bid is strictly higher than 4000 in debt auctions or 66% in equity auctions). A bid is classified as "RA Unrationalizable" if it is not Dominated and if there are no beliefs under which the bid would be undominated for a risk-neutral or risk-averse buyer.[18] A bid is classified as an "Overbid" if it is not Dominated or RA Unrationalizable but it is strictly higher than the Nash equilibrium bid. Otherwise, we classify the bid as an "Underbid."

Figure 10 demonstrates that the larger size of average overbidding that we see within debt auctions is *not* due to bids that are Dominated: the rate of Dominated bids is higher in second-price auctions than in first-price auctions, but within formats, the rates are similar across securities. Thus, the difference between securities is coming from bids in debt auctions that are high, but not so high that a risk-loving buyer would not make them.

In Online Appendix D, we investigate the amount of time that subjects took to make their bidding decisions. There are virtually no differences in response times between treatments. While there can be many interpretations of differences in response times (see Spiliopoulos and Ortmann (2018)), the lack of differences in our study suggests that subjects did not perceive the treatments to have differential complexity.

Result 6. *In formal auctions, overbidding decreases with experience in all treatments except the second-price debt.*

The link between experience and overbidding is presented in Figure 11. While all treatments start with overbidding rates that are higher than 50%, for all treatments other than

[18]This is equivalent to not being Dominated but being strictly higher than the second-price Nash equilibrium bid for the given security. It is straightforward to see this for second-price auctions. For first-price auctions, any bid x between the Nash equilibrium bid of the first-price auction and the Nash equilibrium bid of the second-price auction is rationalizable by beliefs that place probability one on a bid one unit below x. Bids above the second-price Nash equilibrium are not rationalizable for risk-averse buyers in this way because winning at a price above the Nash equilibrium bid leads to a lottery with an expected value that is lower than the buyer's certain outside option.

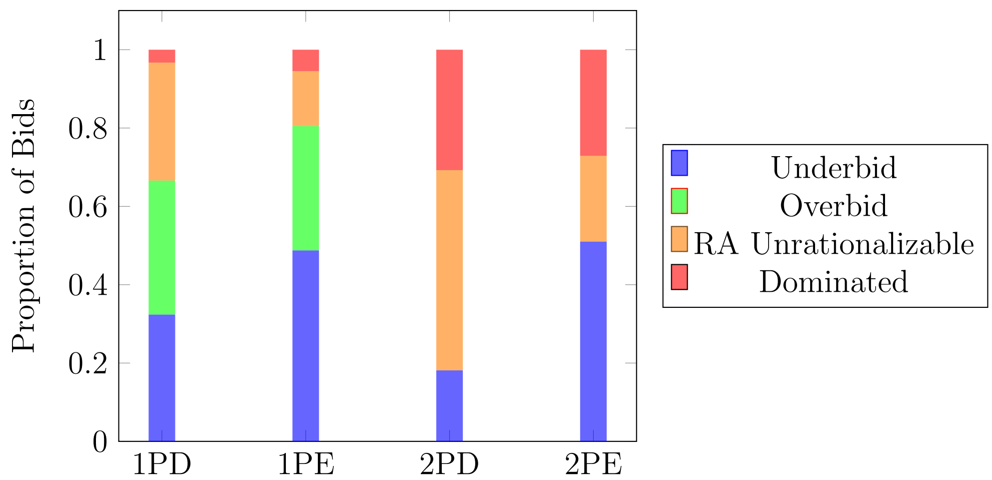


Figure 10: Classification of bids within each treatment. "Dominated" refers to bids that lead to lotteries that are first-order stochastically dominated. "RA Unrationalizable" refers to bids that are not Dominated but cannot be rationalized by a risk-neutral or risk-averse utility function for any beliefs. "Overbid" refers to bids that are not Dominated or RA Unrationalizble, but are higher than the RNNE bid. "Underbid" refers to bids that are equal to or below the RNNE bid.

second-price debt, this rate decreases with experience. We complete this analysis formally in Online Appendix Table 13 to confirm the result and find that the coefficient on experience is negative and significant for first-price debt, first-price equity, and second-price equity, but positive and insignificant for second-price debt. In the three treatments with decreasing overbidding, the coefficients imply overbidding rates of near 50% by the end of the experiment, which is consistent with approximate equilibrium behavior.

We now consider the extent to which overbidding is explained by subjects' individual characteristics. As a first step, it is useful to note that overbidding rates (i.e. the proportion of bids that are strictly higher than an appropriate cutoff) vary across subject and are not always equal to zero or one. This can be seen in Online Appendix Figures 21, 22, and 23, which show rates of bids greater than the Nash equilibrium, rates of bids greater than the

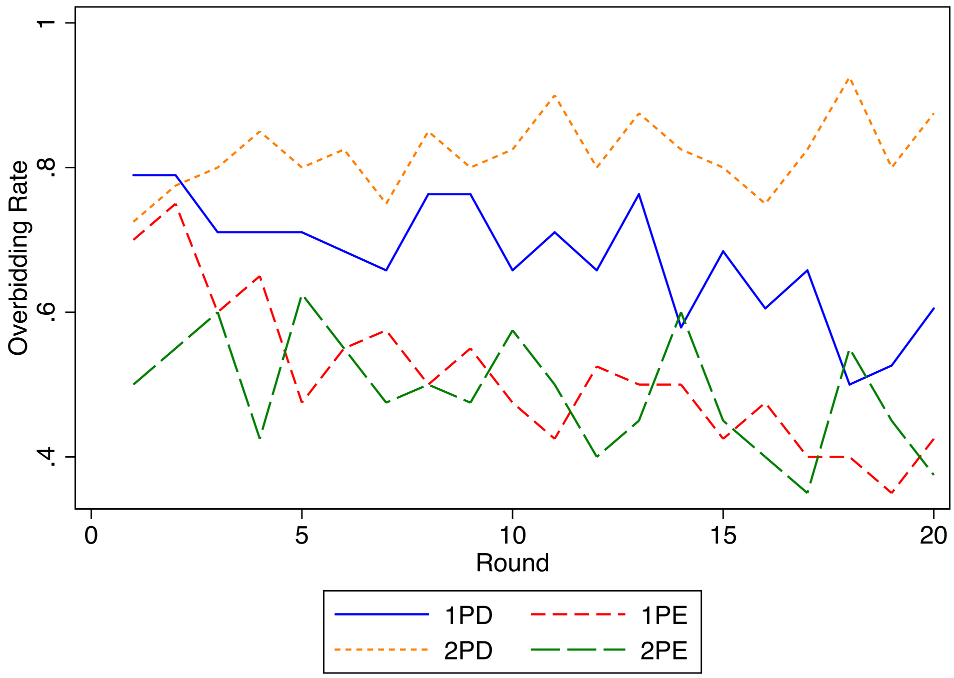


Figure 11: Overbidding rates (relative to RNNE) by round and treatment.

second-price Nash equilibrium, and rates of bids that are first-order stochastically dominated for each of the treatments, respectively. Because these rates are not equal to zero or one, individual characteristics and the treatments can only partially explain overbidding.

Result 7. *Overbidding is uncorrelated with measured risk aversion, negatively correlated with quiz and CRT scores, and positively correlated with confidence about the experiment.*

The relationship between overbidding and subject characteristics is shown in Table 3, in which we regress binary indicators for overbidding on observable characteristics.[19] The dependent variables in the regressions represented in columns (1), (2), and (3) are binary indicators for bidding higher than the Nash equilibrium, bidding higher than second-price

[19]The results are replicated using logistic regressions in Online Appendix Table 14 with patterns of significance generally unchanged.

Nash equilibrium, and making stochastically dominated bids, respectively. Here, we confirm the previously observed relationships between these overbidding rates, treatment, and experience.

Table 3: Overbidding by subject characteristics

	(1) Binary Overbid	(2) RN Unrationalizable	(3) Dominated
1PE	-0.15**	-0.14***	0.016
	(0.059)	(0.052)	(0.025)
2PD	0.17***	0.51***	0.28***
	(0.049)	(0.048)	(0.033)
2PE	-0.17***	0.17***	0.24***
	(0.054)	(0.053)	(0.031)
Round	-0.0071***	-0.0063***	-0.0037***
	(0.0018)	(0.0017)	(0.0012)
Average RA	0.00015	-0.00025	0.0010
	(0.0014)	(0.0013)	(0.00088)
CRT Score	-0.057***	-0.059***	-0.013
	(0.017)	(0.015)	(0.010)
Quiz Score	-0.31***	-0.35***	-0.14***
	(0.079)	(0.083)	(0.048)
Confidence	0.027**	0.027**	0.0025
	(0.011)	(0.010)	(0.0069)
Female	0.0096	0.0045	0.0078
	(0.041)	(0.039)	(0.027)
English	-0.043	-0.0015	0.016
	(0.038)	(0.034)	(0.024)
Economics	-0.0063	-0.027	-0.020
	(0.045)	(0.039)	(0.027)
Age	0.0014	0.0063	0.0014
	(0.0042)	(0.0040)	(0.0029)
Constant	0.81***	0.41***	0.078
	(0.17)	(0.15)	(0.10)
Observations	3160	3160	3160

Notes: Linear regression with standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

The first surprising feature of Table 3 is that our measure of risk aversion does not have a statistically significant relationship with overbidding.[20] This is contrary to our *a priori* intuition: the project that the buyers are bidding for is inherently stochastic, and it should be less valuable for more risk-averse subjects. However, this may not be surprising given the lack of correlation across risk aversion tasks that has previously been found in the experimental literature.[21] We explore this further in Online Appendix Tables 15 and 16, in which we apply the "obviously related instrumental variable" approach proposed in Gillen et al. (2019) to both the average choice and a nonlinear transformation thereof from the Andreoni-Harbaugh task. This approach uses instrumental variables to account for the potential attenuation bias that arises as a result of measurement error in the risk elicitation task. Even with this alternative approach we still do not find a significant relationship between overbidding and measured risk aversion.

While subjects' measured risk aversion does not predict overbidding, several of their other observed characteristics do. Cognitive measures such as the quiz score (the proportion of correct questions, ranging from 0 to 1) and the cognitive reflection test (ranging from 0 to 3) proposed in Frederick (2005) are negatively correlated with overbidding, implying that subjects who better understand the rules of the mechanism are less likely to overbid. Meanwhile, subjects who reported having higher confidence (ranging from 1 to 10) about how

[20]The variable "Average RA" in the regression is defined as the average choice for the Andreoni-Harbaugh risk aversion tasks that the subject completed. This number can range from 0 to 100, with a choice of 50 representing risk neutrality and choices greater than 50 representing risk aversion. We report additional results using a nonlinear transformation of this average (computing a CRRA ρ parameter) in Online Appendix Table 16.

[21]Some previous work has suggested that deviations from risk neutrality with the stakes used in lab experiments may be related to cognitive ability (Dohmen et al., 2010; Benjamin et al., 2013). This is at least partially controlled for in our regressions with the inclusion of quiz and CRT scores. We have also redone the analysis from Table 3 replacing Average RA with dummies representing the subject's quartile of Average RA, allowing us to more flexibly control for observed risk aversion and potentially capture non-monotonicities. We find weak evidence that mildly risk-averse subjects (those in the second quartile) are less likely to overbid. Results are available upon request.

well they understood the tasks were more likely to overbid relative to the Nash equilibrium and to make unrationalizable bids, but were no more likely to make dominated bids. We also control for other demographic variables such as gender, first language, whether the subject was majoring in economics and age. We find no evidence that any of these traits are correlated with overbidding. In Online Appendix B we extend these results to control for the revealed preference indices we measure from the Andreoni-Harbaugh task. We find that while these measures are jointly statistically significant, the individual indices are rarely significant and are difficult to interpret.

5.3 Buyer Behavior in Informal Auctions

We now turn to the analysis of buyer behavior in informal auctions. In these auctions, buyers choose both the type of security they will make a bid with and the value of that bid.

Our first results are about the choice of security in informal auctions and relate to Hypotheses 3 and 4.

Result 8. *In informal auctions, buyers choose to make bids with equity more often than with debt.*

The evidence for Result 8 can be found in Figure 12. The figure shows that buyers choose debt roughly $30 - 40\%$ of the time across signals, and thus clearly rejects the claim of Hypothesis 3 that buyers always choose debt, instead favoring Hypothesis 4. We report a histogram of the rate of choosing equity at the subject level in Online Appendix Figure 24. The distribution appears unimodal, suggesting that subjects mix between securities rather than separating into their preferred security.

Result 9. *In informal auctions, buyers' signal and measured risk aversion are only weakly*

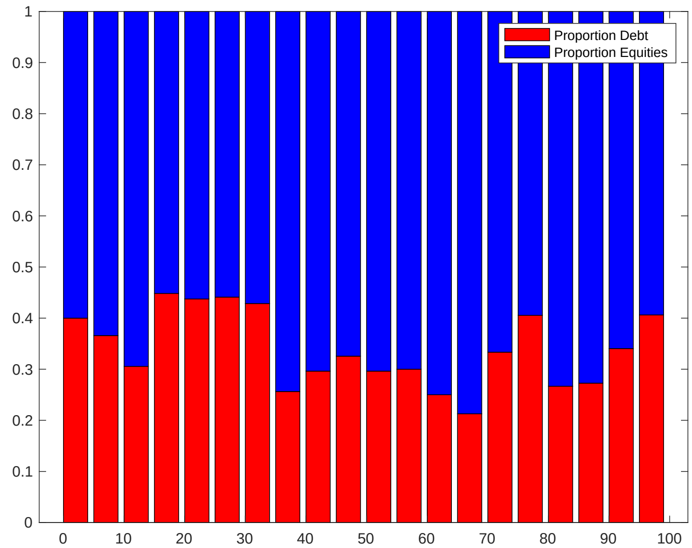


Figure 12: Buyer security choice by signal. Security choices are pooled in windows of 5 signals.

correlated with their choice of security.

Table 4 presents regression analysis showing the relationship between subject characteristics and security choice.[22] Given that only 38 subjects acted as buyers in the informal auctions, we interpret these results with caution.

We find a negative but insignificant relationship between the subject's signal and their likelihood of choosing debt. The estimated relationship suggests that increasing the likelihood that the project generates high revenue from 0 to 100 percent decreases the likelihood of choosing to bid with debt by 10 percentage points. While the relationship is not significant, we note that this is contrary to the logic presented in DKS and discussed in Section 3.3, which argued that buyers will make bids with debt to signal that they have a high valuation.

Similar to the above analysis of overbidding, we find little relationship between our

[22]These results are replicated using logistic regressions in Online Appendix Table 17 with patterns of significance generally unchanged.

Table 4: Security choice by subject characteristics

	(1) Debt	(2) Debt
Signal	-0.00100	-0.0010
	(0.00088)	(0.00089)
Round	0.0036	0.0036
	(0.0041)	(0.0042)
Average RA		-0.0035
		(0.0026)
CRT Score		0.016
		(0.050)
Quiz Score		-0.13
		(0.25)
Confidence		0.030
		(0.042)
Female		0.027
		(0.094)
English		0.18**
		(0.069)
Economics		-0.077
		(0.081)
Age		0.0048
		(0.0064)
Constant	0.35***	0.24
	(0.063)	(0.31)
Observations	760	760

Notes: Linear regression with standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

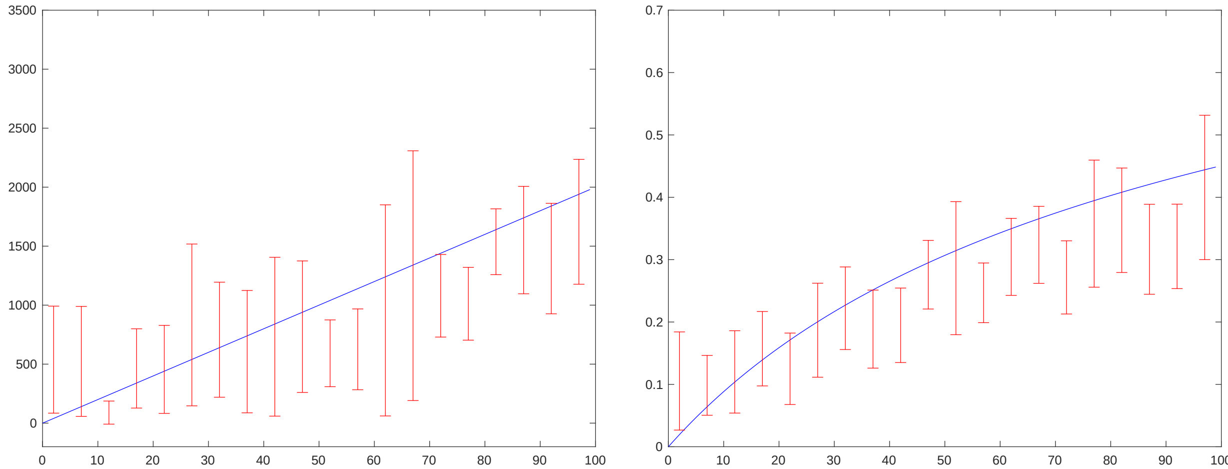
measure of risk aversion and the type of security that the subject chooses. This is surprising because, as noted in Fioriti and Hernandez-Chanto (2021), equity inherently provides more insurance than debt. We again provide additional evidence for the link between choices and risk aversion in Online Appendix Tables 18 and 19. The relationship between security choice and average choice in the Andreoni-Harbaugh task is not significant in any specification, but we do find some evidence that a higher CRRA risk aversion parameter, which we compute as a nonlinear transformation of the average choice in the Andreoni-Harbaugh task, is negatively correlated with choosing debt. However, given the lack of a significant relationship with the average choice in the Andreoni-Harbaugh task, we interpret this relationship with caution. Thus, there is (limited) evidence supporting Hypothesis 4.

The only relationship in Table 4 that is statistically significant is the positive correlation between selecting debt and speaking English as a first language. One (speculative) explanation is that our instructions for debt bids were *relatively* harder to understand for those for whom English is not a first language.

Result 10. *Average bids in the informal auction are close to the equilibrium bids of the associated formal auction.*

Figure 13 reports average bids from informal auctions and compares them with the equilibrium predictions *from a first-price formal auction*. We again average bids in windows of five signals and present 95% confidence intervals. The main observation is that the empirical average of the bids in this treatment are lower and closer to the equilibrium values than the ones obtained in the formal treatments for both security designs. The improvement in fitting equilibrium bids is especially remarkable for debt.

One potential explanation for this arguably more reasonable bidding pattern is a selection effect. In the formal auctions, subjects are required to make bids with a particular security whether or not they like or understand it. It may be the case that those subjects that *would* be overbidding in debt auctions simply choose to bid using equity. However, we see from Table 4 that there is limited selection by observable characteristics into bidding with debt. Furthermore, if selection were a significant driver of the decrease in overbidding in debt we



(a) Debt (b) Equity

Figure 13: Average bids conditional on signal in informal auctions. Bids are averaged in windows of 5 units and presented with 95% confidence intervals. Equilibrium bidding functions from the first-price formal auctions are shown in blue.

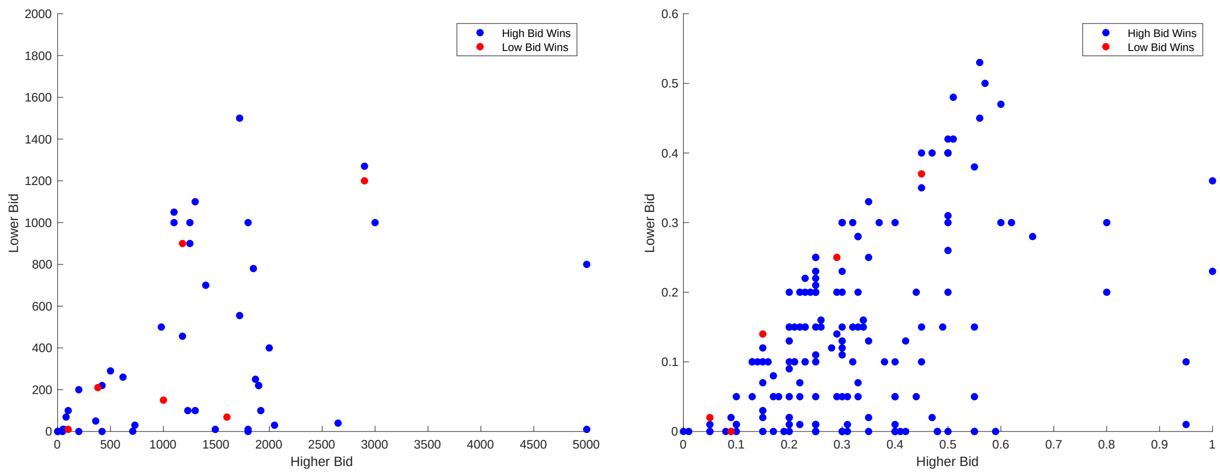
might expect that the correlates of overbidding found in 3 would predict security selection, but that does not seem to be the case.

5.4 Seller Behavior in Informal Auctions

One of the distinctive characteristics of the informal auctions treatment is that the winner's selection is not based on a predetermined rule. Thus, we can evaluate the quality of the seller's decision-making when facing security bids.

Result 11. *In the informal auction when the seller is faced with two bids using the same security, they choose the highest bid.*

Figure 14 displays seller choices for the sample of auctions in which buyers choose the same security to express their bids: Panel 14a shows the sample for debt and Panel 14b



(a) Two Debt Bids

(b) Two Equity Bids

Figure 14: Seller behavior when facing two bids from the same security.

shows the sample for equity. In both figures, the x axis corresponds to the higher bid; thus, all points lie below the 45-degree line by construction. Blue points correspond to those cases in which the seller chooses the highest index in the corresponding ordered set, whereas the red points correspond to the cases where the lowest ones were chosen. Under both securities, sellers overwhelmingly choose the bid with the highest index. This seems intuitive and suggests that sellers do not believe that bids are non-monotonic in the signal.

Result 12. *In the informal auction, when the seller is faced with two bids using different securities, one of which dominates the other, they choose the dominant bid.*

In contrast, Figure 15 shows the seller's selection when he faces bids from different sets of securities. While it can be difficult to rank bids made with different securities, in some case the ranking *should* be obvious. For instance, if one buyer makes an equity bid of 40% (giving a minimum payment of 800 points) and the other buyer makes a debt bid of 600 points, the seller should always choose the equity bid. Figure 15 demonstrates that this is generally the

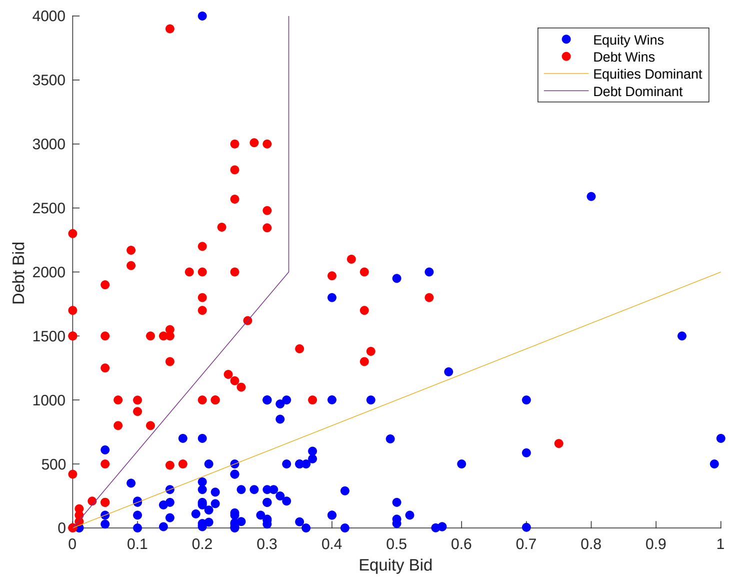


Figure 15: Seller behavior when facing two bids from different securities.

case. For bidding pairs that are between the purple line and the y axis, the highest possible equity payment is lower than the lowest possible debt payment. For bidding pairs that are below the yellow line, the highest possible debt payment is lower than the lowest equity payment. In the figure, a red dot corresponds to the case where the seller chooses the bid in debt, whereas a blue dot corresponds to a case where the seller chooses the equity bid. It is immediate to see that in the domination regions, the seller almost always chooses correctly. Moreover, in the ambiguous region, sellers do not seem to have a strong preference for either type of security. The only identifiable pattern is a smooth gradient, shifting from the choice of one security to the other.

6 Discussion

6.1 Behavioral Models of Overbidding

To better understand the factors driving overbidding in our experiment, we turn to behavioral explanations that have been presented in the experimental literature. We consider what these models of bidding imply for security-bid auctions and determine whether such models (or any combination thereof) can explain behavior across treatments in our experiment. That is, we ask whether previously proposed models can explain our data *holding the model and any parameters fixed across treatments*. The main patterns we seek to explain are (1) overbidding for all signals in first- and second-price debt auctions, (2) overbidding for low and high signals in first- and second-price equity auctions, (3) bidding close to or below equilibrium for intermediate signals in first- and second-price equity auctions.

First, we note that if non-standard utility functions were the main driver of overbidding, we should not expect to see overbidding change with experience. However, the decrease in overbidding with experience is documented in Result 6. Thus, *preference*-based explanations can at best partially explain overbidding.

One explanation for overbidding in first-price auctions that has been thoroughly studied in the experimental literature is subjects' risk aversion. Early work showed that risk aversion can lead to overbidding relative to the risk-neutral Nash equilibrium (Cox et al., 1988). However, later work showed that in some cases, there is still overbidding in auctions where risk aversion should lead to underbidding (Kagel and Levin, 1993; Cason, 1995). More recently, Goeree et al. (2002) showed that risk aversion, when combined with quantal response equilibrium, can explain the data from discrete first-price auctions. In our experiment, the object for which subjects bid for are lotteries. Thus, in our second-price auctions, risk aversion should *lower* bids relative to the RNNE. Furthermore, the large number of bids that cannot be rationalized by *any* beliefs for a risk-neutral or risk-averse decision maker (see Figure 10) should make one skeptical that risk aversion is an important driver of overbidding in this setting. In any case, Table 3 shows that risk aversion (as measured by the Andreoni-Harbaugh task) is uncorrelated with overbidding.

The apparently noisy bidding discussed in Section 5.1 suggests that models allowing for mistakes, such as McKelvey and Palfrey's (1995) quantal response equilibrium (QRE) may be useful to organize the data. QRE has been successfully used to explain bidding behavior, including overbidding, in experimental auctions (Goeree et al., 2002; Bajari and Hortacsu, 2005; Camerer et al., 2016). In Online Appendix C, we investigate how well logit QRE can explain our results. We find that QRE *cannot* explain the patterns of average bids that we observe. While QRE does lead to overbidding for most parameter values, it does not explain the level of overbidding that we observe for high signals in both second-price treatments. Furthermore, the average bidding functions in quantal response equilibria are generally flatter than those that we observe in our data. We also estimate the QRE parameter λ, which captures how noisy decision-making is, using the methods proposed in Camerer et al. (2016). We can reject the null hypothesis that a single logit QRE parameter can explain the data from all four treatments. This is primarily due to the difference between the parameter estimated for second-price equity and the other three treatments.

Many papers have proposed preferences that are "non-standard" as a source of overbidding in auctions. Morgan et al. (2003) proposes a model of spite as a driver of overbidding in second-price auctions and compares it to joy of winning. Andreoni et al. (2007), Cooper and Fang (2008), and Kirchkamp and Mill (2021) present experimental evidence in favor of spite as a significant determinant of overbidding. There are several reasons why spite alone cannot explain the data from our experiment. First, spite is generally presented as an explanation for overbidding in second-price auctions, so it does not explain our overbidding in first-price debt auctions. Second, spite generally leads to overbidding for low signals (so that the buyer can lower the payoff of their opponent when they do not expect to win). Figure 9 shows substantial overbidding even for very high signals when the buyer should reasonably expect to win. Finally, it is unclear why spite should lead to overbidding for intermediate signals in second-price debt auctions, but does not lead to overbidding for intermediate signals in second-price equity auctions. Another non-standard model that has been used to explain overbidding is regret theory, but this should not lead to overbidding in second-price auctions or to substantial overbidding for low signals (Filiz-Ozbay and Ozbay, 2007).

Probability weighting is another important behavioral model that is relevant when studying auctions (Quiggin, 1982; Tversky and Kahneman, 1992). Probability weighting admits a wide variety of implications for bidding behavior. Armantier and Treich (2009a) shows that "star-shaped" probability weighting functions lead to overbidding, but Keskin (2016) shows that the most commonly used "inverse S-shaped" probability weighting functions lead to underbidding for low valuations and overbidding for high valuations. The introduction of probability weighting into our setting involves additional difficulties because the object subjects are bidding for is itself a lottery. Thus, the auction forms a compound lottery and probability weighting can affect bids even in the second-price format. However, there is reason to be skeptical that probability weighting is the main driver behind bidding patterns in our auction. First, there is no probability weighting function that can rationalize overbidding in the second-price auctions for high signals. Because weighting functions are bounded above by one, buyers should not exceed a bid of 4000 in debt auctions or 66% in equity auctions. Second, it would require extreme overweighting of low probabilities to generate the overbidding seen for low signals in the second-price debt treatment.

Some authors have proposed other variations in the concept of equilibrium to explain patterns of overbidding. Eyster and Rabin (2005) formalizes the concept of "cursed equilibrium" to explain overbidding in common-value auctions, but this explanation applies only to settings where players' private information should affect each others' valuations (thus, it cannot explain overbidding in the private value auctions we study in this paper). Ockenfels and Selten (2005) introduce the concept of "impulse balance equilibrium" in which a buyer bids to balance upwards and downwards impulses. This is extended in Pezanis-Christou and Wu (2019) to the concept of "naive impulse balance equilibrium." But both of these concepts predict no overbidding in second price auctions and thus cannot explain the overbidding in our second-price debt treatment. Following Stahl and Wilson (1994), Nagel (1995), and Stahl and Wilson (1995), Crawford and Iriberri (2007) uses "level-k" thinking to explain behavior in auctions. The naivete of L_0 agents can be expressed by assuming either a uniform-random or a truthful behavior. In either case, this would lead to average bids that are equal to or below equilibrium bids for the highest signals in second-price auctions. Figure 9 shows that this is not borne out by the data.

It may be the case that subjects' misperceptions about the game or their competition lead to overbidding. Armantier and Treich (2009b) states that overbidding in first-price auctions is a consequence of the fact that people underestimate their probability of winning. However, this does not explain our overbidding in second-price auctions, which have a dominant strategy. Georganas et al. (2017) presents a model in which buyers both misperceive the distribution of bids and believe that they will pay a fraction of the realized price. Such a model allows for overbidding in both first- and second-price auctions, but does not explain the difference between overbidding in equity and debt.

Finally, we discuss whether some combination of non-classical explanations can explain the data. The idea that subjects have a "joy of winning" is a fairly parsimonious justification that explains most overbidding, including for both low signals in first-price auctions and high signals in second-price auctions. However, the joy of winning would also lead to overbidding for intermediate signals in equity auctions. Some models such as risk aversion or (pessimistic) probability weighting would predict lower valuations for those intermediate signals, but the negative effect on bids should be *stronger* for debt auctions than for equity auctions because debt auctions tend to have lower payments in the bad state. Thus, even the combination of these features with the joy of winning does not explain the data, and we remain puzzled about exactly what existing models can explain our results.

6.2 Implications for Security-Bid Auction Design

The literature on security-bid auctions has clear theoretical predictions in environments where buyers are risk-neutral, implementation costs are fixed, there are no moral hazard incentives, and there are no externalities. The main takeaway is that sellers must use securities that are tied more tightly to buyers' valuations (i.e., steeper securities) if they want to maximize revenue (DeMarzo et al., 2005). Additionally, the literature shows that the auction format has a lower effect on revenue relative to the security design. Nonetheless, for this result to hold buyers need to understand that, aside from accounting for the strategic uncertainty entailed by the auction game, steeper securities extract more interim surplus but provide more insurance. When buyers fail to fully internalize this and depart from the Nash equilibrium, a pattern of overbidding and noisy bidding emerges, distorting the results over revenue.

First, as shown in Result 3, the auction format can affect revenue differently in the presence of noisy bidding: it negatively affects the second-price auction and positively the first-price auction, because it increases the variance of the bid distribution. Then, if this effect is substantial, flatter securities under a first-price auction could potentially perform better than steeper securities under a second-price auction. Furthermore, noisy bidding diminishes the value of steepness because it decreases the likelihood that the buyer with the highest bid is also the one whose project will generate the highest revenue. This challenges the view that steeper securities unequivocally yield higher expected revenue, regardless of the auction format.

Second, Results 5 and 6 show that overbidding is persistent across securities and formats, being more prominent under debt than under equity. Interestingly, the differences in overbidding cannot be explained by an easy measure of buyer naivete. For instance, the fraction of dominated bids is roughly the same across securities, conditional on the format. This suggests that the complexity of the security design, along with the bounded rationality of buyers, plays a fundamental role in explaining these patterns. This observation is important because although in real life these auctions will be played by sophisticated buyers, the way they would engage in deep hierarchies of beliefs to determine their optimal behavior would matter more depending on the security design used by the seller. This is perhaps an explanation of why more complex securities such as convertible debt or levered equity are less used in practice in favor of equity and combinations of cash and equity (Skrzypacz, 2013).

With respect to informal auctions, the security-bid literature is less clear. On the one hand, DKS argues that under risk neutrality, the only signaling equilibrium that survives is a pooling equilibrium in which all buyers submit bids using the flattest security. Nonetheless, this result is not in line with the empirical evidence or the early literature on signaling equilibrium in takeover informal auctions (Hansen, 1987; Fishman, 1989; Eckbo et al., 1990).[23] On the other hand, Fioriti and Hernandez-Chanto (2021) argues it is not true that buyers with high valuations are always eager to choose a flatter security if they were risk-averse, since in such a case they would forgo the insurance provided by steeper securities. Our results conclusively reject the hypothesis from DKS, while only offering lukewarm support to the hypothesis from Fioriti and Hernandez-Chanto (2021). This suggests that in informal auctions there are other factors, perhaps related to the intrinsic strategic uncertainty of the game, that deserve to be explored more deeply from a theoretical and empirical perspective.

Moreover, our results indicate that new *behavioral* models of overbidding are needed for securities auctions. While some of our results may be a result of our sample being primarily made up of university undergraduates, there is substantial and growing evidence that even experienced professionals are subject to behavioral biases (see Malmendier (2018) and the citations therein for many examples). If this is the case, then it will be valuable to determine which biases are relevant for securities auctions and how they affect the design of optimal auctions.

Finally, our experimental design offers the advantage of comparability in terms of formal vs informal mechanisms, auction formats, and security designs. As such, it offers a unified framework to simultaneously test many of the theoretical predictions in the security-bid literature. Hence, the mixed results we obtain are a call for the necessity of increasing the experimental and empirical analysis of such noteworthy—yet not very well analyzed—allocation mechanisms in future research.

[23]For instance, Fishman (1989) shows that initial buyers use flatter securities (or cash) as a preemptive strategy, with the idea that only buyers with high valuation would choose the flatter security, since steeper securities are less costly for low-valuation buyers.

7 Conclusion

Our paper provides a unified experimental framework to study formal and informal security-bid auctions under debt and equity. This type of auction has the feature that the final payment to the seller is contingent on the realization of the project (asset) being auctioned, and, thus, can be contracted upon it. Unlike standard cash auctions in which buyers learn their valuation at the time to submit their bids, in these auctions, buyers receive a signal about the potential realization of the project. Hence, buyers essentially bid for a lottery, whose final prizes depend on the security design and the auction format utilized by the seller.

We find that when the seller commits to sell the project using a first- or a second-price auction (i.e., following a formal auction) buyers overbid in debt under all signals, while they overbid in equity under low and high signals but underbid for intermediate signals—i.e., the signals for which the project is more risky. The prominent overbidding in debt makes the auctions under this security deliver the highest expected revenue to the seller despite being "flatter" than equity, contradicting the results predicted by theory. We find that this overbidding pattern decreases with experience, except in the second-price debt auction, and is less present in buyers that understand better the structure of the security—i.e., those with high scores in the quiz and the cognitive reflection test. Interestingly, the overbidding across securities is similar, conditional on the format, if we look at the rate at which buyers submit ex-post-dominated bids. The main differences in overbidding come from bids that are higher than what the RNNE would prescribe, but consistent with bids that could have been chosen by risk-loving buyers.

We also find that the effect of noisy overbidding affects both auction formats by increasing the variance of bids: it increases the revenue in the first-price auction while decreases it in the second-price auction. This has an implication for how formal mechanisms are ranked, since a first-price auction under flatter securities like debt can yield a higher revenue than a second-price auction under a steeper security like equity.

We also analyze buyers' and sellers' behaviors in informal auctions. Here, the seller does not commit to use a predefined format to allocate the project, and, hence, buyers can freely choose any security to express their bids. This implies that the security design is on the hands of the buyers, who may use it to signal their types to the seller. We showed that buyers behave closely to the RNNE equilibrium of their respective chosen security, despite not being "forced" to bid under that security, and that sellers successfully choose dominant bids whenever they are faced with them. The last two observations are remarkable because informal auctions entail a game that arguably has higher cognitive demands than the one in formal auctions. Nonetheless, despite their higher rational consistency, informal auctions experimentally yield the lowest expected revenue across our treatments.

Our paper presented a thorough analysis of experimental security-bid auctions, which allowed us to test agents' behavior across selling mechanisms, formats, and securities. Some of the theoretical predictions are confirmed, while others are challenged. For some others we remain puzzled about which drivers can explain our results. We interpret the latter as an indication that more empirical and experimental analysis are needed to understand better these complex auctions that allocate millions of dollars every year around the world.

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Internet Appendix

A Theoretical equilibrium outcomes

A.1 First-price equilibria

Here, we confirm that the bidding strategies that we state in Hypothesis 2 form an equilibrium.

First, consider the first-price debt auction and suppose that the other buyer is bidding according to

$$d_{1,-i}(p_{-i}) = 2000p_{-i}.$$

Then, given a signal of p_i, the expected payoffs of making a bid $d \leqslant 2000$ are

$$\left(1 - \frac{d}{2000}\right)(6000p_i + 2000(1 - p_i) - 2000 - d).$$

First-order conditions give

$$\left(\frac{d_1^*}{2000}\right)(-1) + \left(\frac{1}{2000}\right)(6000p_i + 2000(1 - p_i) - 2000 - d_1^*) = 0,$$

which simplifies to $d_1^* = 2000p_i$ and confirms that the proposed strategy profile is an equilibrium.

Next, consider the first-price equity auction and suppose that the other buyer is bidding according to

$$e_{1,-i}(p_{-i}) = \frac{p_{-i} - 0.5\ln(2p_{-i}+1)}{p_{-i}}.$$

We can define $p_{-i}(e)$ as the inverse of this bidding function so that given a signal of p_i, the expected payoffs of making a bid of e are

$$p_{-i}(e)[(1-e)(6000p_i + 2000(1-p_i)) - 2000].$$

Given that

$$p'_{-i}(e) = \frac{2(p_{-i}(e))^2(1+2p_{-i}(e))}{(1+2p_{-i}(e))\ln(2p_{-i}(e)+1) - 2p_{-i}(e)},$$

the first-order conditions of the buyer's problem can be written as

$$\frac{2(p_{-i}(e^*))^2(1+2p_{-i}(e^*))}{(1+2p_{-i}(e^*))\ln(2p_{-i}(e^*)+1) - 2p_{-i}(e^*)}[(1-e^*)(6000p_i + 2000(1-p_i)) - 2000]$$
$$= p_{-i}(e^*)(6000p_i + 2000(1-p_i)).$$

Thus, for the proposed strategy profile to be an equilibrium, it must be the case that

$$\left[\frac{2p_i^2(1+2p_i)}{(1+2p_i)\ln(2p_i+1) - 2p_i}\right]\left[\left(1 - \frac{p_i - 0.5\ln(2p_i+1)}{p_i}\right)(6000p_i + 2000(1-p_i)) - 2000\right]$$
$$= p_i(6000p_i + 2000(1-p_i))$$

which one can check always holds. Thus, the proposed strategy profile is an equilibrium.

A.2 Equilibrium Surplus Distribution

The equilibria described in Hypotheses 1 and 2 are all increasing and symmetric. Thus, these equilibria are efficient and expected total surplus is

$$E[\text{Total Surplus}] = \int_0^1 [6000p + 2000(1-p) - 2000](2p)dp = \frac{8000}{3}.$$

Using the bidding functions found in the hypotheses, we can compute expected revenue for the risk-neutral Nash equilibrium for each of the treatments (note that the predicted revenue for informal auctions is the same as that of first-price debt auctions).

$$\begin{aligned} E[\text{Revenue}|\text{First-price Debt}] &= \int_0^1 (2000p)(2p)dp \\ &= \frac{4000}{3} \end{aligned}$$

$$\begin{aligned} E[\text{Revenue}|\text{First-price Equity}] &= \int_0^1 \left(\frac{p - 0.5\ln(2p+1)}{p}\right)(6000p + 2000(1-p))(2p)dp \\ &= \frac{20000}{3} - 4500\ln(3) \\ &\approx 1722.9 \end{aligned}$$

$$
\begin{aligned}
E[\text{Revenue}|\text{Second-price Debt}] = &\int_0^{\frac{1}{2}} \left[\int_0^{p_2} (4000p_1) \left(\frac{1}{p_2} \right) dp_1 \right] (2p_2) dp_2 \\
&+ \int_{\frac{1}{2}}^{1} \left[\int_0^{\frac{1}{2}} (4000p_1) \left(\frac{1}{p_2} \right) dp_1 \right] (2p_2) dp_2 \\
&+ \int_{\frac{1}{2}}^{1} \left[\int_{\frac{1}{2}}^{p_2} \left[\left(6000 - \frac{2000}{p_1} \right) p_2 + 2000(1-p_2) \right] \left(\frac{1}{p_2} \right) dp_1 \right] (2p_2) dp_2 \\
=& \frac{500}{3} + 500 + \frac{6250}{3} - 2000\ln(2) \\
=& 2750 - 2000\ln(2) \\
\approx& 1363.7
\end{aligned}
$$

$$
\begin{aligned}
E[\text{Revenue}|\text{Second-price Equity}] &= \int_0^{1} \left[\int_0^{p_2} \frac{2p_1}{2p_1+1} [6000p_2 + 2000(1-p_2)] \left(\frac{1}{p_2} \right) dp_1 \right] (2p_2) dp_2 \\
&= \frac{20000}{3} - 4500\ln(3) \\
&\approx 1722.9
\end{aligned}
$$

Expected buyer surplus is given by total surplus minus revenue, so we have

$$
\begin{aligned}
E[\text{Buyer Surplus}|\text{First-price Debt}] &= \frac{8000}{3} - \frac{4000}{3} \\
&= \frac{4000}{3}
\end{aligned}
$$

$$E[\text{Buyer Surplus}|\text{First-price Equity}] = \frac{8000}{3} - \left(\frac{20000}{3} - 4500\ln(3)\right)$$
$$= 4500\ln(3) - 4000$$

$$E[\text{Buyer Surplus}|\text{Second-price Debt}] = \frac{8000}{3} - (2750 - 2000\ln(2))$$
$$= 2000\ln(2) - \frac{250}{3}$$

$$E[\text{Buyer Surplus}|\text{Second-price Equity}] = \frac{8000}{3} - \left(\frac{20000}{3} - 4500\ln(3)\right)$$
$$= 4500\ln(3) - 4000$$

B Revealed Preference Results

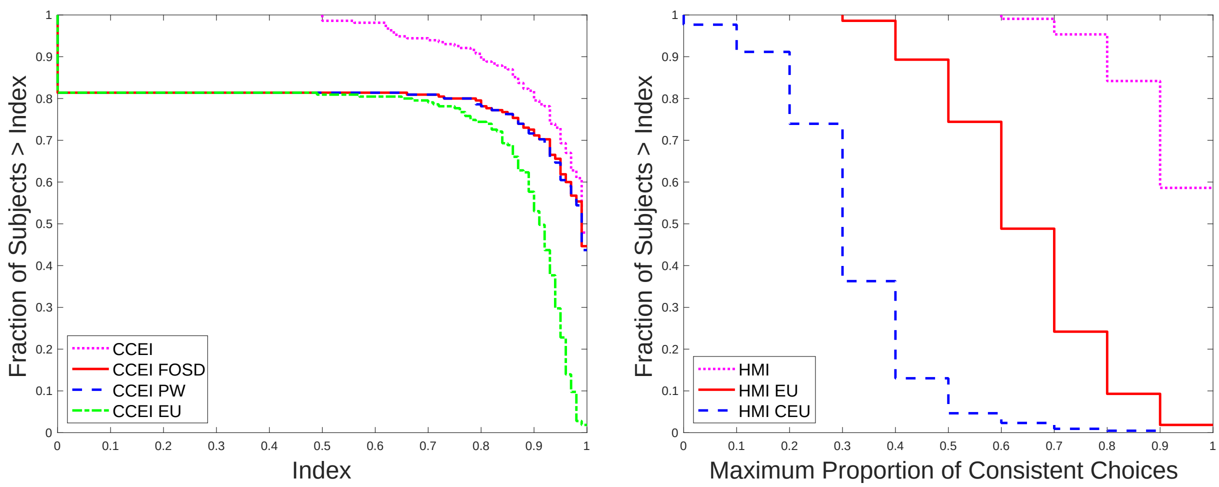
In this section, we report results related to revealed preference measures that we derive from subjects' choices in the Andreoni-Harbaugh task. We first discuss the measurements that we make and then show how those measurements correlate with behavior in auctions.

The first class of indices that we discuss are Critical Cost Efficiency Indices (CCEIs). A CCEI is an index between 0 and 1 that is meant to capture how close a set of choices is to being rationalized by some model. The original CCEI proposed in Afriat (1973) is a measure of how close a set of decisions is to being rationalized by a strictly monotonic utility function. Formally, a set of choices has a CCEI of e if e is the highest number such that there exists a utility function that assigns higher utility to each choice than it does to all options in the budget scaled by a factor of e. One can further define CCEIs for specific *families* of utility functions, measuring how close a set of choices is to being rationalized by some member of that family. Breig and Feldman (2024) uses intuitions from Polisson et al. (2020) to show how to calculate CCEI indices for utility functions respecting first-order stochastic dominance, probability-weighting utility functions, and expected utility functions using the Andreoni-Harbaugh task.

The second class of indices that we discuss is Houtman-Maks Indices (HMIs) (Houtman and Maks, 1985). The classic HMI measures the proportion of choices from a data set that can be rationalized by a strictly monotonic utility function. Breig and Feldman (2022) extend this index within the context of the Androeni-Harbaugh task to show how to compute the proportion of choices that are consistent with expected utility and concave expected utility.

Figure 16 reports the distributions of the indices for all 215 subjects in our experiment. While the specific quantitative results differ from previous work (as is to be expected, given different budgets and different numbers of choices), the qualitative patterns are very similar.

Considering CCEI indices, the CCEI index for models respecting first-order stochastic dominance is much lower than the classic index, and the index for expected utility is much lower than that for probability weighting. The results using HMI indices match those of Breig and Feldman (2022), with significant gaps between each of the indices. As discussed in Breig and Feldman (2022), the HMI CEU index is particularly low because being consistent with concave expected utility requires that the *exact* same choice be made for all budgets with the same maximal prize. Because subjects choose from each budget twice in this experiment, even minimal decision noise leads to indices below 0.5



(a) CCEI Indices

(b) HMI Indices

Figure 16: Distributions of revealed preference indices

In Table 5, we present the empirical relationship between the measured revealed preference indices and overbidding in formal auctions, still controlling for the treatment variables and subject characteristics from Table 3. We caution that the individual coefficients can be difficult to interpret due to the high correlation and similar interpretations of the variables. However, we conduct F-tests for whether the measures as a whole are significantly correlated with bidding behavior, and we find that the relationship is significant for overbidding at the

5% level and for making dominated bids at the 1% level.

Table 5: Overbidding by Revealed Preference Indices

	(1) Binary Overbid	(2) RN Unrationalizable	(3) Dominated
HMI	-0.42	-0.40	-0.31
	(0.32)	(0.29)	(0.24)
HMI EU	0.072	0.024	-0.19
	(0.21)	(0.18)	(0.12)
HMI CEU	0.013	-0.011	-0.013
	(0.17)	(0.17)	(0.13)
CCEI	0.20	0.32	0.44*
	(0.31)	(0.32)	(0.25)
CCEI FOSD	3.35*	-0.81	-1.62
	(1.81)	(3.23)	(1.99)
CCEI PW	-4.30**	0.48	1.07
	(1.92)	(3.25)	(2.00)
CCEI EU	0.92*	0.15	0.44
	(0.52)	(0.46)	(0.28)
Other Controls	Yes	Yes	Yes
F-test p-value	.046	.142	.009
Observations	3160	3160	3160

Notes: Linear regression with standard errors clustered at the subject level. "Other Controls" refers to all independent variables used in Table 3, including treatment variables. The "F-test p-value" refers to the p-value arising from the F-test that coefficients on all seven revealed preference indices are zero. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

C Quantal Response Equilibrium

In this section, we discuss how our results relate to the logit formulation of Quantal Response Equilibrium (QRE) (McKelvey and Palfrey, 1995). We take two complementary approaches to establish this relationship. First, we estimate the quantal response noise parameters that best fit the data from our experiments. With this, we can statistically test whether the data across all four treatments is likely to have been generated by a single QRE noise parameter. Second, using the structure of the formal auctions, we compute quantal response equilibria for various parameters and for each game. We generate average bidding functions based on these equilibria and compare them to our empirical average bidding functions.

In a quantal response equilibrium, decision-makers know the distribution of actions that they will face in a game, but do not always make choices that maximize their payoffs. Instead, they randomize in a way that makes choices leading to higher payoffs more likely than choices leading to lower payoffs. In particular, decision-makers choose *as if* the utility they receive from each option is equal to the numerical payoff from that option plus a random draw from an extreme value distribution.

To formalize the application of QRE to the formal auctions presented in this paper, we need some additional notation. For each treatment $k \in \{1\text{PE}, 1\text{PE}, 2\text{PD}, 2\text{PE}\}$, we define the set of possible bids as B_k. Thus, $B_{1\text{PD}} = B_{2\text{PD}} = \{0, 0.5, 1, \ldots, 59.5, 60\}$ and $B_{1\text{PE}} = B_{2\text{PE}} = \{0, 0.01, 0.02, \ldots, 0.99, 1\}$.[24,25] We refer to a bid from buyer i as b_i and their private signal as

[24] The QRE noise parameter is not invariant to the scale of payoffs, so in order to allow for comparison to other results, in this section we state both payoffs and debt bids in terms of Australian dollars rather than experimental points.

[25] While $B_{1\text{PE}}$ and B_{2PE} correctly represent the choices available to subjects in our experiment, subjects in the two debt treatments could make bids with any integer between 0 and 6000. We focus on bids made with multiples of 50 in order to simplify the analysis. The vast majority ($\approx$85%) of bids were already made in these multiples of 50, but for our empirical analysis, we round all bids to the nearest multiple of 50.

p_i. With these definitions, the probability that buyer i bids b is

$$P(b_i = b|p_i) = \frac{\exp\left(\lambda \mathbb{E}[u_k(b, p_i)|p_i]\right)}{\sum_{b' \in B^k} \exp\left(\lambda \mathbb{E}[u_k(b', p_i)|p_i]\right)} \tag{3}$$

where $\mathbb{E}[u_k(b, p_i)|p_i]$ is the expected payoff for buyer i when they make bid b in treatment k. For instance, in the case of first-price debt auctions, we have

$$\begin{aligned} \mathbb{E}[u_{1\mathrm{PD}}(b, p_i)|p_i] = {} & [\mathbb{P}(b_j < b) + 0.5\mathbb{P}(b_j = b)]\left((1-p_i)\max\{20 - b, 0\} + p_i(60 - b)\right) \\ & + [\mathbb{P}(b < b_j) + 0.5\mathbb{P}(b_j = b)]\,(20). \end{aligned}$$

For this to be an equilibrium, we require that beliefs match the equilibrium distribution of bids, so

$$\mathbb{P}(b_j < b) = \int \left[\sum_{b' : b' < b} P(b_i = b'|p_i) \right] f(p_i) dp_i.$$

The parameter λ in equation (3) captures the amount of noise in buyers' bids. We estimate the best fit for λ within each treatment and then jointly for all treatments in Section C.1. We then show average bidding functions under QRE (computed using a fixed-point algorithm) across treatments and for various values of λ in Section C.2.

C.1 Estimation of Quantal Response Equilibrium Parameters

In this section, we estimate the QRE λ parameter that best fits the distribution of bids in our formal auction treatments. We follow Camerer et al. (2016) in using the intuition from Bajari and Hortacsu (2005) to estimate these parameters. In particular, under the assumption that subjects are playing a QRE for some λ, then the empirical distribution of bids is a consistent estimator for the equilibrium distribution of bids. We can then use this empirical distribution to compute subjects' expected payoffs from each potential bid, allowing us to estimate the maximum likelihood estimator for λ.

In what follows, we describe the procedure to estimate the QRE parameters in detail. Throughout, we use k to refer to treatment (1PD, 1PE, 2PD, or 2PE), i to refer to subject, and t to refer to round.

1. Given N_k, the number of subjects in treatment k, compute the empirical probability mass function $\hat{f}^k(b)$ for all $b \in B_k$:

$$\hat{f}^k(b) = \frac{\sum\limits_{i,t} \mathbb{1}(b_{k,i,t} = b)}{20N_k}$$

2. Define expected payoffs for bid b under signal p as

$$\begin{aligned}
\hat{u}_{1\text{PD}}(b, p_i) &= \left[\sum_{\{b' \in B_{1\text{PD}} : b' < b\}} \hat{f}^{1\text{PD}}(b') + 0.5 \hat{f}^{1\text{PD}}(b) \right] ((1 - p_i) \max(20 - b, 0) + p_i(60 - b)) \\
&+ \left[\sum_{\{b' \in B_{1\text{PD}} : b < b'\}} \hat{f}^{1\text{PD}}(b') + 0.5 \hat{f}^{1\text{PD}}(b) \right] (20) \\
\hat{u}_{1\text{PE}}(b, p_i) &= \left[\sum_{\{b' \in B_{1\text{PE}} : b' < b\}} \hat{f}^{1\text{PE}}(b') + 0.5 \hat{f}^{1\text{PE}}(b) \right] (1 - b) ((1 - p_i)(20) + p_i(60)) \\
&+ \left[\sum_{\{b' \in B_{1\text{PE}} : b < b'\}} \hat{f}^{1\text{PE}}(b') + 0.5 \hat{f}^{1\text{PE}}(b) \right] (20) \\
\hat{u}_{2\text{PD}}(b, p_i) &= \sum_{\{b' \in B_{2\text{PD}} : b' < b\}} \hat{f}^{2\text{PD}}(b') ((1 - p_i) \max(20 - b', 0) + p_i(60 - b')) \\
&+ \hat{f}^{2\text{PD}}(b) \left[0.5 ((1 - p_i) \max(20 - b, 0) + p_i(60 - b)) + 0.5(20) \right] \\
&+ \left[\sum_{\{b' \in B_{2\text{PD}} : b' > b\}} \hat{f}^{2\text{PD}}(b') \right] (20) \\
\hat{u}_{2\text{PE}}(b, p_i) &= \sum_{\{b' \in B_{2\text{PE}} : b' < b\}} \hat{f}^{2\text{PE}}(b')(1 - b') ((1 - p_i)(20) + p_i(60)) \\
&+ \hat{f}^{2\text{PE}}(b) \left[0.5(1 - b) ((1 - p_i)(20) + p_i(60)) + 0.5(20) \right] \\
&+ \left[\sum_{\{b' \in B_{2\text{PE}} : b' > b\}} \hat{f}^{2\text{PE}}(b') \right] (20)
\end{aligned}$$

3. Conditional on the QRE parameter λ and signal p, define choice probabilities for each treatment k and each bid $b \in B_k$ as

$$\mathbb{P}_k(b; p, \lambda) = \frac{\exp(\lambda \hat{u}_k(b, p))}{\sum_{b' \in B_k} \exp(\lambda \hat{u}_k(b', p))}$$

4. Solve for the maximum likelihood estimator for each treatment, as well as the pooled estimator:

$$\hat{\lambda}_k = \underset{\lambda}{\operatorname{argmax}} \sum_{i,t} \ln\left(\mathbb{P}_k\left(\hat{b}_{k,i,t}; p_{k,i,t}, \lambda\right)\right)$$

$$\hat{\lambda}_{\text{Pooled}} = \underset{\lambda}{\operatorname{argmax}} \sum_{k,i,t} \ln\left(\mathbb{P}_k\left(\hat{b}_{k,i,t}; p_{k,i,t}, \lambda\right)\right)$$

Carrying out this process gives us the estimates that we report in Table 6. We compute confidence intervals by inverting the likelihood ratio test. We find that the estimated values of λ for the first-price debt, first-price equity, second-price treatments, and the pooled estimate are quite close to each other. However, λ_{2PE} is roughly three times the size of the other estimates. A likelihood ratio test rejects equality of the parameter λ across all four treatments with a p-value less than 0.01.

Table 6: Quantal Response Equilibrium Estimates

	1PD	1PE	2PD	2PE	Pooled
$\hat{\lambda}$	0.129	0.136	0.144	0.427	0.145
Confidence Interval	[0.115,0.142]	[0.12,0.151]	[0.118,0.171]	[0.368,0.489]	[0.135,0.154]
Bidders	38	40	40	40	158
Observations	760	800	800	800	3160
Log Likelihood	-3397	-3464	-3770	-3541	-14230

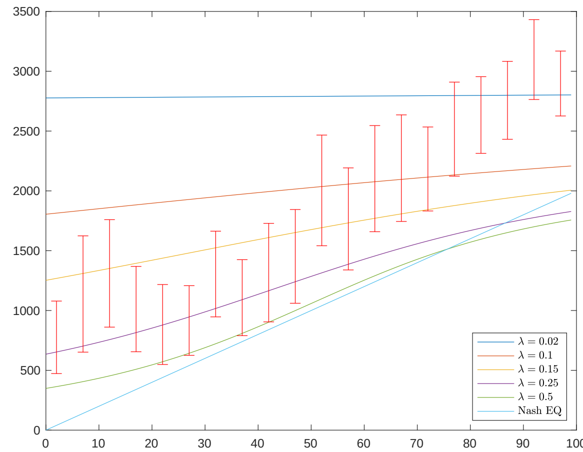
C.2 Computation of Quantal Response Equilibria

In this section, we report the results of computing bidding probabilities for various QRE parameters in each game. We compute these probabilities iteratively. For each value of λ, we initialize bidding probabilities to be uniform over all bids.[26] With this distribution and for each signal, we compute the expected payoff for each potential bid. We then update the bidding probabilities by plugging the expected payoffs and λ into Equation 3. This process is iterated until the bidding functions reach a fixed point.

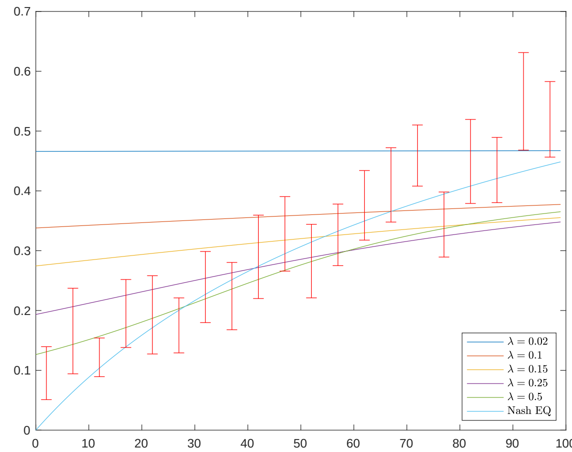
Figure 17 shows the average bidding functions generated by QRE equilibria for various values of λ. For λ near zero, bidding probabilities are close to uniform across all possible bids, leading to average bids that are near 3000 in debt auctions and 0.5 in equity auctions. As λ increases, the average bidding functions generally get closer to the Nash Equilibrium bidding functions (although this is not uniformly the case).

While there are some interesting similarities between the average bidding functions implied by QRE and our empirical average bids, the overall patterns do not seem to match. QRE's noisy bidding combined with the fact that all bids are bounded below by zero leads to overbidding for low signals, as we find in our data. However, we find that no value of λ can match the overbidding that we observe for high signals across treatments. In fact, for many values of λ, QRE leads to *underbidding* for high signals relative to the RNNE.

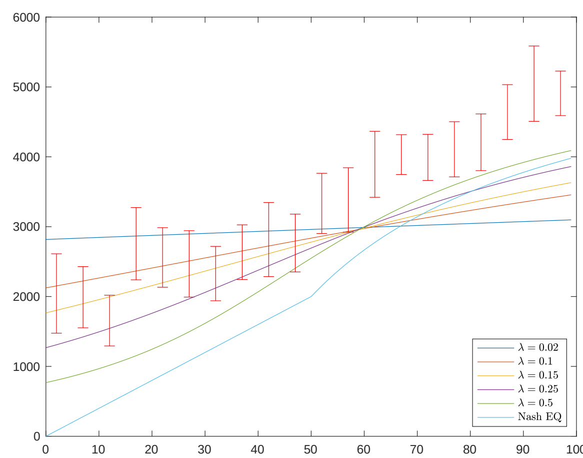
[26] In this section we again restrict all debt bids to be made in multiples of 50.



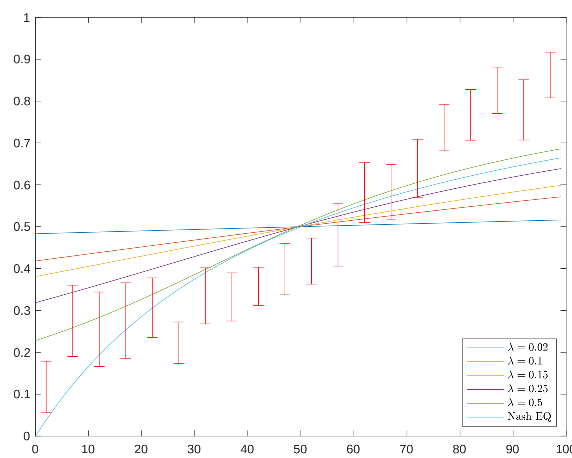
(a) First-price debt



(b) First-price equity



(c) Second-price debt



(d) Second-price equity

Figure 17: Average bidding functions based on Quantal Response Equilibria for various parameters and for each type of formal auction. The QRE are presented alongside the Nash Equilibria and the empirical averages for bids conditional on signal, as in Figure 9.

D Decision Times

In this section, we report results related to the time subjects took when making their bids. Due to technical difficulties, decision times were not recorded for the final two sessions, which consisted of first- and second-price equity auctions. Thus, the dataset consists of 38 subjects in first-price debt auctions, 26 subjects in first-price equity auctions, 40 subjects in second-price debt auctions, and 28 subjects in second-price equity auctions. We find no evidence of differences in time taken to make bids between treatments.

We show the empirical distribution of bidding times in Figure 18. There is no obvious difference between the treatments in this distribution. We carry out a Kruskall-Wallis test of the equality of distributions of bidding times and bidding times averaged at the subject level. Neither test rejects equality of distributions (p-values of 0.29 and 0.83, respectively).

In Table 7, we regress bidding time on treatment dummies and controls for experience. None of the treatment coefficients are significant at the 10% level, and the F-test for equality of all treatments gives a p-value of 0.76.

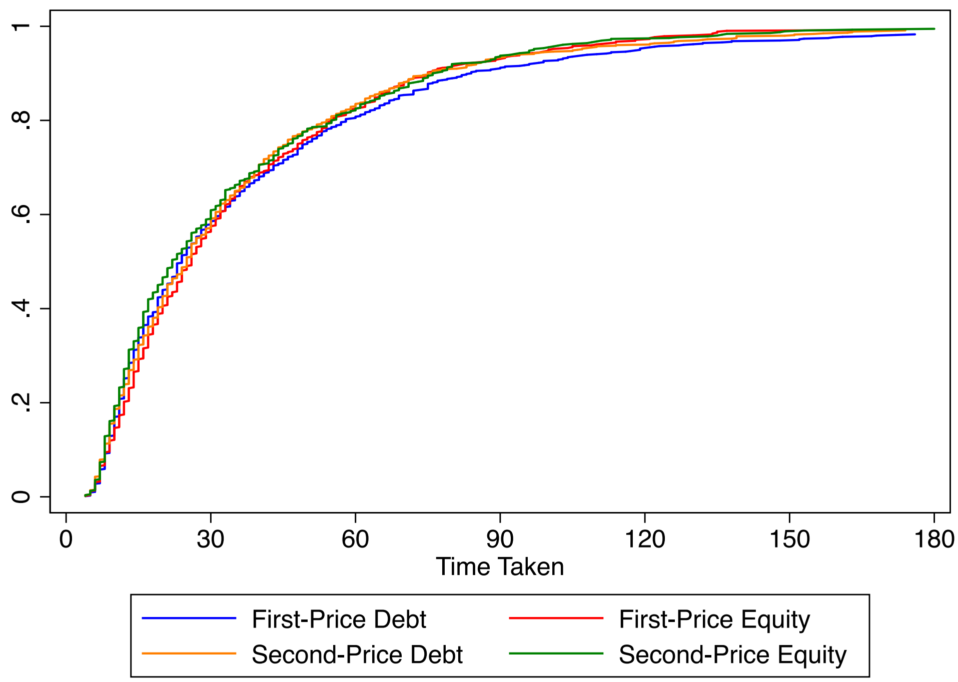


Figure 18: CDFs of bidding times by treatment. CDFs are truncated at 180 seconds.

Table 7: Time taken by treatment and round

	(1) Time Taken	(2) Time Taken
1PE	-3.46	-3.46
	(5.29)	(5.29)
2PD	-3.81	-3.81
	(4.62)	(4.62)
2PE	-5.37	-5.37
	(5.12)	(5.12)
Round		-7.70***
		(0.76)
Round Squared		0.26***
		(0.030)
Constant	39.8***	83.5***
	(3.78)	(6.07)
Observations	2640	2640

Notes: Linear regression with standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

E Additional Results

Table 8: Summary Statistics

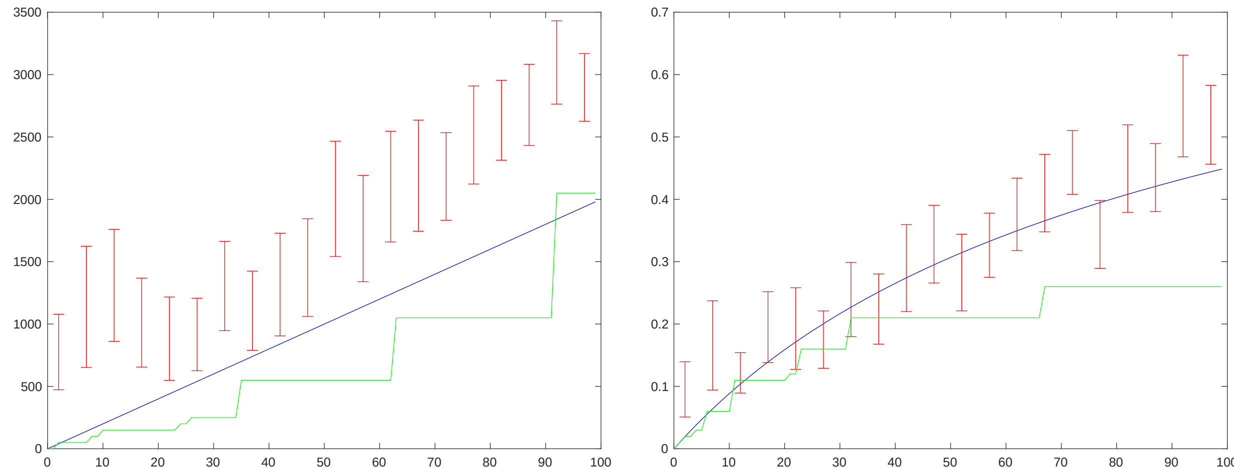
	Mean	Std. Dev.
CRT Score	1.45	1.14
Female	0.60	0.49
Age	22.76	4.27
English	0.41	0.49
Economics	0.33	0.47
Subjects	215.00	

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

Table 9: Summary Statistics from the Andreoni-Harbaugh Task

	Mean	Std. Dev.
16,000 Max Prize, 0.4 Max Probability (first choice)	57.11	23.61
20,000 Max Prize, 0.5 Max Probability (first choice)	59.98	23.56
12,000 Max Prize, 0.6 Max Probability (first choice)	60.25	21.31
8,000 Max Prize, 0.8 Max Probability (first choice)	56.94	20.87
10,000 Max Prize, 1.0 Max Probability (first choice)	53.50	26.84
16,000 Max Prize, 0.4 Max Probability (second choice)	60.58	23.30
20,000 Max Prize, 0.5 Max Probability (second choice)	62.57	22.88
12,000 Max Prize, 0.6 Max Probability (second choice)	61.93	19.89
8,000 Max Prize, 0.8 Max Probability (second choice)	60.53	19.75
19,000 Max Prize, 1.0 Max Probability (second choice)	56.75	22.10
Subjects	215.00	

Notes: This table reports summary statistics for the average choice made for each Andreoni-Harbaugh task. Each subject saw two copies of five unique budgets. The ordering of the five budgets was randomized at the subject level, but no subject saw the second copy of a budget before seeing all five first copies. The reported choice is the proportion out of 100 of the budget allocated towards increasing the probability of receiving the prize, so a choice of 70 from the first budget is a $\frac{70}{100} \times 0.4 = 0.28$ chance of receiving $\left(1 - \frac{70}{100}\right) \times 16000 = 4800$ points. The expected value is maximized at a choice of 50, so the reported averages are consistent with mild risk aversion.



(a) Debt (b) Equity

Figure 19: Empirical best responses in formal first-price auctions. Equilibria are given in blue and empirical best responses are given in green. Bids are averaged in windows of 5 units and presented with 95% confidence intervals. Generally, empirical best responses are below Nash Equilibrium bids, which are themselves below the empirical average of bids conditional on signals.

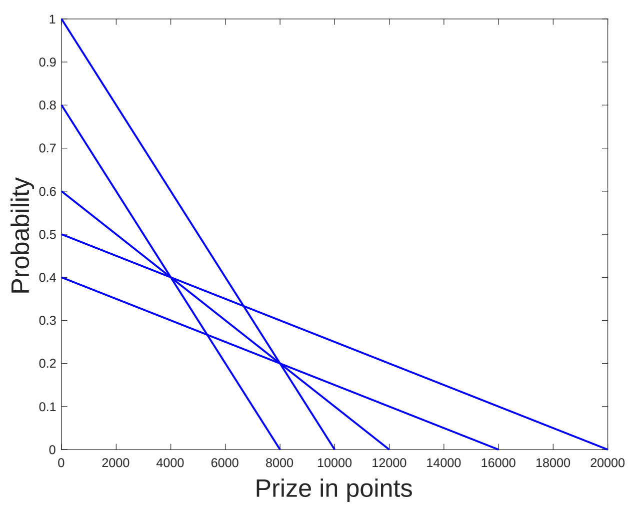


Figure 20: Budgets from the Andreoni-Harbaugh task. Each budget was seen twice, for a total of ten choices. One hundred points corresponds to one dollar. The expected value-maximizing choice is to choose the middle of the budget line.

Table 10: Interim revenue: Last 10 Rounds

	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue
1PE	-246.5**	-262.1***	-262.1***	-262.1***
	(111.8)	(88.8)	(88.5)	(89.0)
2PD	5.60	105.8	105.7	105.8
	(105.5)	(90.9)	(90.6)	(91.0)
2PE	-763.4***	-723.5***	-723.6***	-723.5***
	(108.9)	(92.4)	(92.5)	(92.6)
Informal	-750.9***	-766.3***	-766.3***	-766.3***
	(97.4)	(86.5)	(86.0)	(86.1)
Potential Surplus		0.64***	0.64***	0.64***
		(0.030)	(0.030)	(0.031)
Round			-21.3**	
			(10.1)	
Constant	2089.5***	426.2***	757.8***	523.6***
	(69.6)	(100.0)	(185.4)	(136.0)
Round FE	No	No	No	Yes
Observations	980	980	980	980

Notes: Linear regression with robust standard errors using data from only Rounds 11 to 20. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1. This table replicates the results from Table 1, restricting only to data in the last 10 rounds (when subjects had gained experience). The general patterns remain, with debt-bid auctions generating substantially more revenue than informal and equity-bid auctions.

Table 11: Surplus: Last 10 Rounds

	(1) Surplus	(2) Surplus	(3) Surplus	(4) Surplus
1PE	22.4	-1.60	-1.60	-1.56
	(111.2)	(55.2)	(55.2)	(55.1)
2PD	-182.9	-28.5	-28.5	-28.7
	(113.3)	(57.7)	(57.7)	(57.6)
2PE	42.1	103.5**	103.5**	103.4*
	(110.3)	(52.6)	(52.7)	(52.9)
Informal	-66.7	-90.5	-90.5	-90.5
	(114.2)	(63.1)	(63.1)	(63.0)
Potential Surplus		0.98***	0.98***	0.98***
		(0.015)	(0.015)	(0.016)
Round			1.34	
			(6.13)	
Constant	2353.7***	-208.3***	-229.2**	-155.9**
	(80.5)	(53.2)	(112.3)	(71.3)
Round FE	No	No	No	Yes
Observations	980	980	980	980

Notes: Linear regression with robust standard errors using data from only Rounds 11 to 20. Significance indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
This table replicated the results from Table 2, restricting only to data in the last 10 rounds (when subjects had gained experience). The point predictions are similar, although the standard errors are larger due to including less data.

Table 12: Overbidding

	(1) Overbid	(2) Overbid	(3) Overbid	(4) Overbid
Signal	-11.3	-0.0039***	-26.7***	-0.0095***
	(6.93)	(0.00091)	(7.61)	(0.0012)
Signal Squared	0.17***	0.000038***	0.19**	0.00011***
	(0.061)	(0.0000096)	(0.077)	(0.000012)
Constant	790.3***	0.10***	1885.7***	0.13***
	(192.1)	(0.026)	(206.0)	(0.034)
Treatment	1PD	1PE	2PD	2PE
Subject FE	Yes	Yes	Yes	Yes
Observations	760	800	800	800

Notes: Linear regression with standard errors clustered at the subject level. The dependent variable is the subject's bid minus the RNNE bid. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
This table studies the potential nonlinear effect of different signals on average overbidding. The regression is run separately for each type of formal auction. In all cases, overbidding is a convex function, and the implied minimum level of overbidding is reached at intermediate signal levels (from 33 to 70).

Table 13: Overbidding

	(1) Binary Overbid	(2) Binary Overbid	(3) Binary Overbid	(4) Binary Overbid
Round	-0.010***	-0.015***	0.0036	-0.0067**
	(0.0039)	(0.0031)	(0.0034)	(0.0031)
Constant	0.79***	0.67***	0.78***	0.56***
	(0.057)	(0.051)	(0.052)	(0.044)
Treatment	1PD	1PE	2PD	2PE
Subject FE	Yes	Yes	Yes	Yes
Observations	760	800	800	800

Notes: Linear regression with standard errors clustered at the subject level. The dependent variable is the subject's bid minus the RNNE bid. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1. This table studies the effects of experience on propensity to overbid separately for each treatment. The relationship is negative and statistically significant for all treatments, except for second-price debt-bid auctions.

Table 14: Overbidding by subject characteristics (Logit)

	(1) Binary Overbid	(2) RN Unrationalizable	(3) Dominated
1PE	-0.66**	-0.80***	0.49
	(0.27)	(0.29)	(0.51)
2PD	0.98***	2.52***	2.66***
	(0.29)	(0.29)	(0.35)
2PE	-0.75***	0.78***	2.47***
	(0.24)	(0.25)	(0.35)
Round	-0.035***	-0.035***	-0.030***
	(0.0087)	(0.0100)	(0.0099)
Average RA	0.0011	-0.0014	0.0091
	(0.0067)	(0.0071)	(0.0070)
CRT Score	-0.27***	-0.33***	-0.086
	(0.083)	(0.087)	(0.090)
Quiz Score	-1.57***	-1.83***	-1.24***
	(0.43)	(0.46)	(0.40)
Confidence	0.13**	0.16***	0.040
	(0.053)	(0.058)	(0.052)
Female	0.040	0.019	0.056
	(0.20)	(0.21)	(0.22)
English	-0.18	-0.018	0.11
	(0.18)	(0.19)	(0.20)
Economics	-0.013	-0.15	-0.26
	(0.22)	(0.22)	(0.22)
Age	0.0047	0.030	0.021
	(0.021)	(0.023)	(0.027)
Constant	1.47*	-0.35	-3.43***
	(0.80)	(0.85)	(0.93)
Observations	3160	3160	3160

Notes: Logistic regression with standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
This table reports the Logit version of the linear regression shown in Table 3. Patters of signs and statistical significance are essentially identical across the two tables.

Table 15: Overbidding by Subject Characteristics

	(1) Binary Overbid	(2) Binary Overbid	(3) Binary Overbid
Average RA	0.00015		
	(0.0014)		
Average RA (round 1-5)		0.00090	
		(0.0015)	
Average RA (round 6-10)		-0.00086	
		(0.0017)	
Instrumented RA			0.00020
			(0.0018)
Other Controls	Yes	Yes	Yes
ORIV	No	No	Yes
Observations	3160	3160	6320

Notes: Linear regression with standard errors clustered at the subject level. "Other Controls" refers to all variables included in Table 3. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

This table reports the linear relationship between the propensity to overbid and average choices from the Andreoni-Harbaugh task. In the first column, the independent variable is the average proportion of the AH budget assigned to probability across all ten choices from this task. In the second column, the independent variables are the same average computed over the first five tasks (made from the 5 unique budgets) and the second five tasks (each of which is a second copy of one of the 5 unique budgets). The third column uses the Obviously Related Instrumental Variable approach from Gillen et al. (2019) in which each observation is duplicated. In half of those observations, the average choices in the first five rounds is used to instrument for the average choice in rounds 6-10, and in the other half of the observations, the reverse is carried out.

Table 16: Overbidding by Subject Characteristics

	(1) Binary Overbid	(2) Binary Overbid	(3) Binary Overbid
CRRA ρ	0.010		
	(0.026)		
CRRA ρ (round 1-5)		-0.026*	
		(0.015)	
CRRA ρ (round 6-10)		0.037	
		(0.023)	
Instrumented CRRA ρ			0.0084
			(0.033)
Other Controls	Yes	Yes	Yes
ORIV	No	No	Yes
Observations	3160	3160	6320

Notes: Linear regression with standard errors clustered at the subject level. "Other Controls" refers to all variables included in Table 3. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

This table reports the linear relationship between the propensity to overbid and a nonlinear transformation of average choices from the Andreoni-Harbaugh task. In particular, as mentioned in Breig and Feldman (2024), CRRA decision makers with parameter ρ would assign the constant proportion $\frac{1-\rho}{2-\rho}$ of their budget on increasing the prize chosen. Thus, labeling the average Andreoni-Harbaugh choice as $\bar{AH}$, one estimate of ρ is $\frac{1-2\bar{AH}}{1-\bar{AH}}$. This estimate is the independent variable included in the first column. The second column uses the same procedure to estimate two values of ρ, the first from the average of the first five Andreoni-Harbaugh choices and the second from the average of rounds 6-10. Both of these estimates are then included as regressions. Finally, the third column again estimates two values of ρ in the same was as was used for the second column. We then use the Obviously Related Instrumental Variable approach from Gillen et al. (2019) in which each observation is duplicated. In half of these observations, the estimated value of ρ from the first five rounds is used to instrument for the second five rounds, while in the other half of the observations the reverse is carried out.

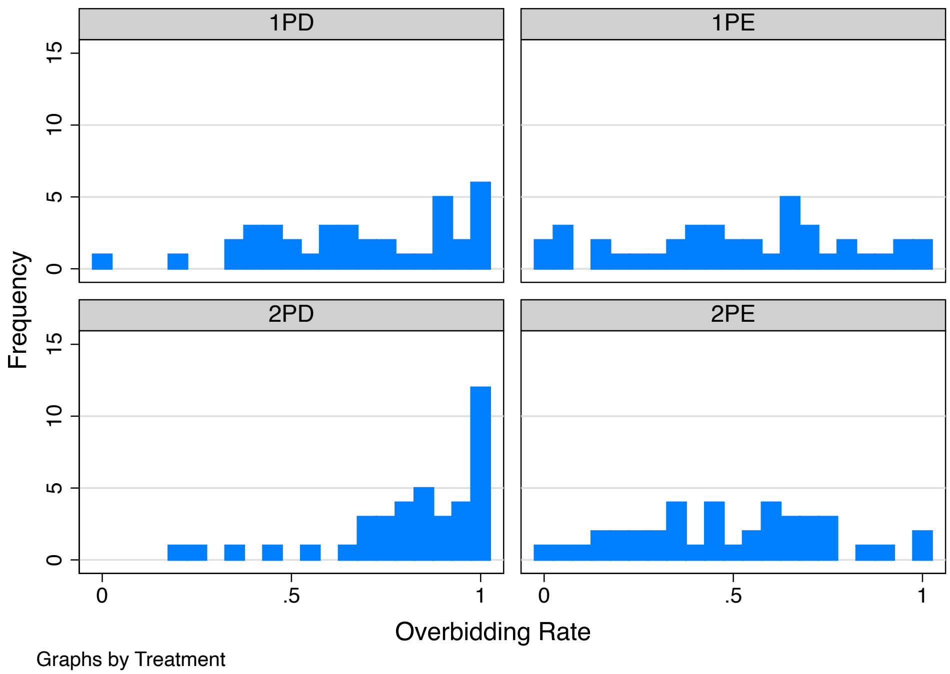


Figure 21: Subject-Level Overbidding Rates by Treatment. This figure shows how many subjects overbid at various rates within each treatment. The overbidding rate for a subject is computed as the number of bids that were strictly over the Nash equilibrium bid divided by the total number of bids (20 in each treatment). Thus, the rightmost three values of the first panel of the figure shows that in the first-price debt treatment, six subjects overbid in every round, two subjects overbid in exactly 19 out of 20 rounds, and five subjects overbid in exactly 18 out of 20 rounds. Similarly, the leftmost three values of the second panel of the figure show that in the first-price equity treatment, two subjects never overbid, three subjects overbid in exactly 1 out of 20 rounds, and zero subjects overbid in exactly 2 out of 20 rounds.

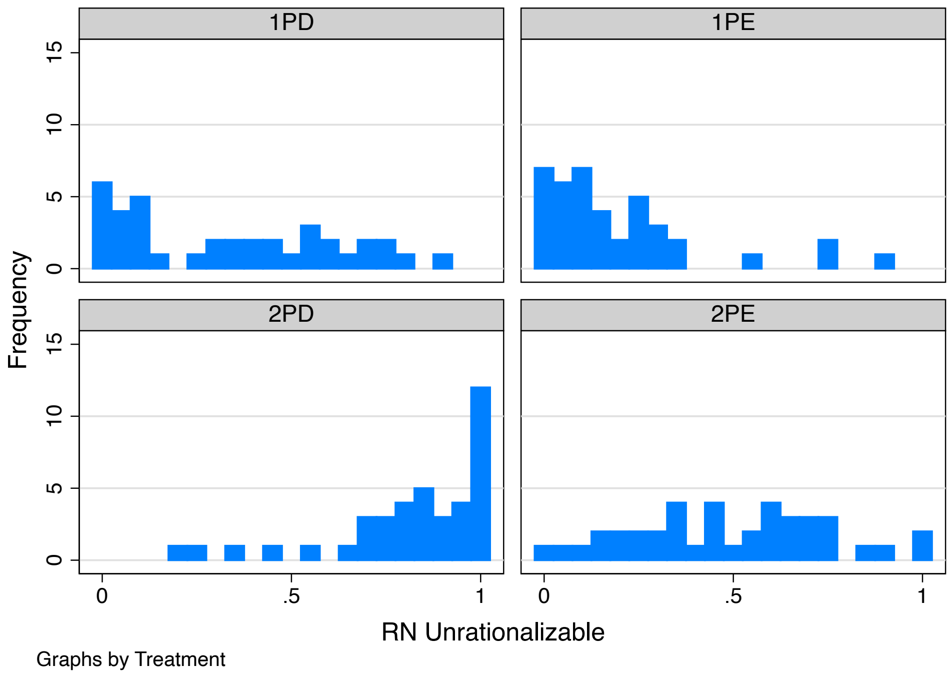


Figure 22: Subject-Level Risk-Neutral Unrationalizable Rates by Treatment. This figure shows how many subjects make risk-neutral unrationalizable bids at various rates within each treatment. A bid is defined as unrationalizable if it there is no combination of beliefs and concave utility function that would rationalize the bid for a given signal. In practice and for a given security, this is equivalent to bidding higher than the risk-neutral Nash Equilibrium of the second-price auction using that security. The rate is then computed as the number of risk-neutral unrationalizable bids divided by the total number of bids (20 in each treatment). Thus, the rightmost three values of the first panel of the figure show that in the first-price debt treatment, no subjects made risk-neutral unrationalizable bids in 19 or more rounds, while one subject made unrationalizable bids in exactly 18 out of 20 rounds. Similarly, the leftmost three values of the second panel of the figure show that in the first-price equity treatment, seven subjects never made a risk-neutral unrationalizable bid, six subjects made risk-neutral unrationalizable bids in exactly 1 out of 20 rounds, and seven subjects made exactly risk-neutral unrationalizable bids in exactly 2 out of 20 rounds.

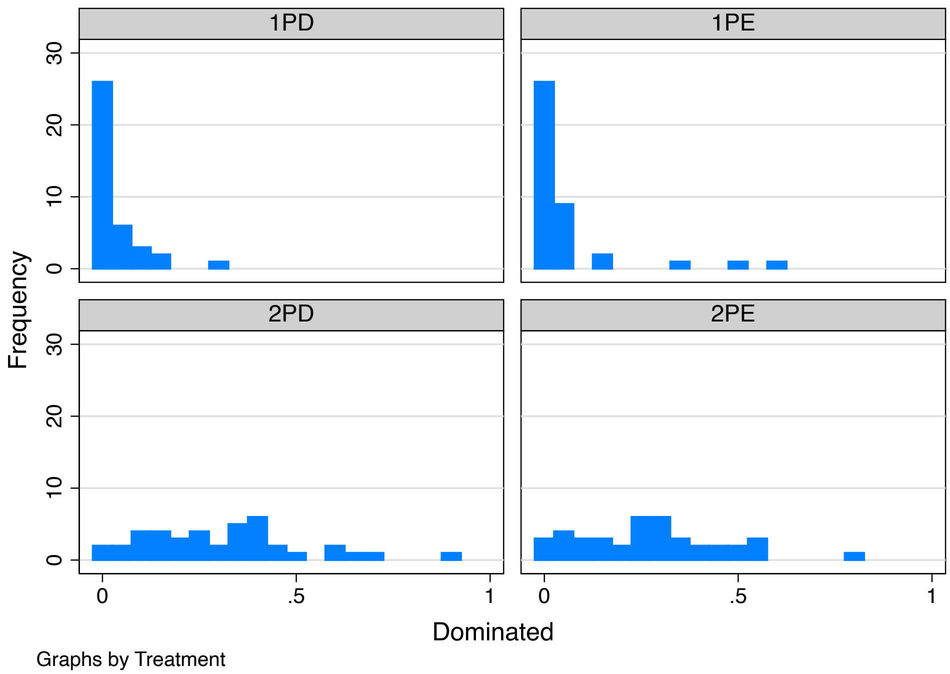


Figure 23: Subject-Level Dominated Rates by Treatment. This figure shows how many subjects made dominated bids at various rates within each treatment. The dominated rate for a subject is computed as the number of bids that were strictly over 4000 (in debt treatments) or 66% (in equity treatments) divided by the total number of bids (20 in each treatment). Thus, the leftmost three values of the first panel of the figure shows that in the first-price debt treatment, twenty-six subjects never made a dominated bid, six subjects made a dominated bid in exactly 1 out of 20 rounds, and three subjects made a dominated bid in exactly 2 out of 20 rounds. Similarly, the leftmost three values of the second panel of the figure show that in the first-price equity treatment, twenty-six subjects never made a dominated bid, nine subjects made a dominated bid in exactly 1 out of 20 rounds, and zero subjects made dominated bids in exactly 2 out of 20 rounds.

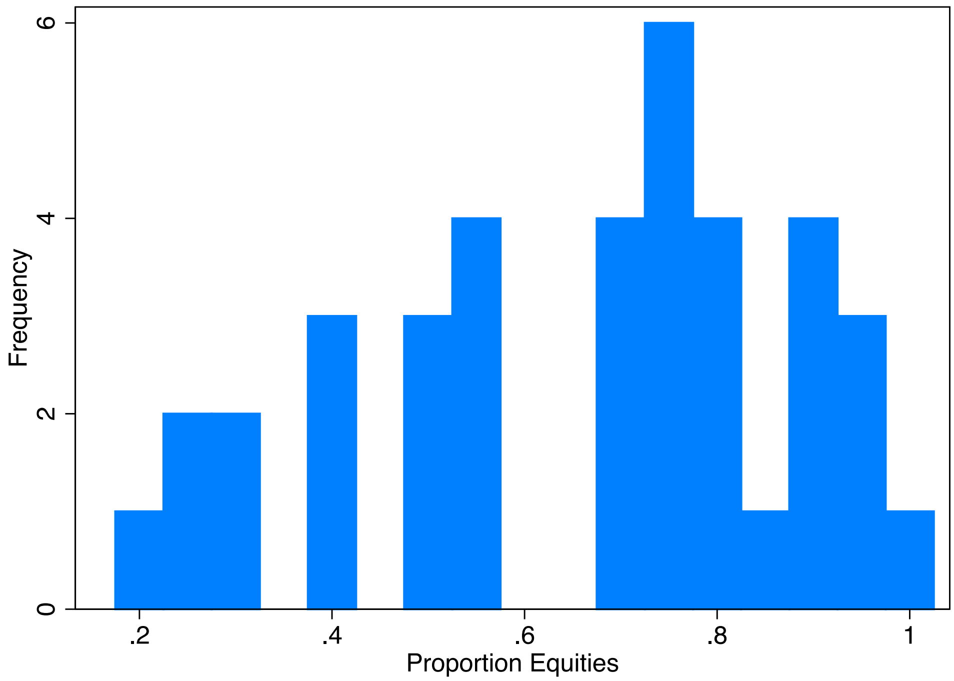


Figure 24: Proportion Equity by Subject. This figure shows how many subjects chose to make bids using equity at various rates in the informal auction treatment. The rate of choosing equity for a subject is computed as the number of rounds in which a bid was made using equity divided by the number of rounds in which the subject acted as a buyer (this varied from subject to subject). Thus, the figure shows that one subject chose to use equities in roughly twenty percent of the opportunities they had to do so, while three subjects chose to use equities in roughly forty percent of the opportunities they had to do so.

Table 17: Buyer security choice by subject characteristics

	(1) Debt	(2) Debt
Signal	-0.0044	-0.0048
	(0.0039)	(0.0041)
Round	0.016	0.017
	(0.018)	(0.019)
Average RA		-0.016
		(0.013)
CRT Score		0.080
		(0.24)
Quiz Score		-0.65
		(1.17)
Confidence		0.13
		(0.20)
Female		0.13
		(0.43)
English		0.80**
		(0.33)
Economics		-0.36
		(0.38)
Age		0.018
		(0.031)
Constant	-0.61**	-1.01
	(0.28)	(1.47)
Observations	760	760

Notes: Logistic regression with standard errors clustered at the subject level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
This table reports the Logit version of the linear regression shown in Table 4. Patters of signs and statistical significance are essentially identical across the two tables.

Table 18: Buyers' Security Choice by Subject Characteristics

	(1) Debt	(2) Debt	(3) Debt
Average RA	-0.0035		
	(0.0026)		
Average RA (round 1-5)		-0.0028	
		(0.0038)	
Average RA (round 6-10)		-0.00047	
		(0.0048)	
Instrumented RA			-0.0048
			(0.0032)
Other Controls	Yes	Yes	Yes
ORIV	No	No	Yes
Observations	760	760	1520

Notes: Linear regression with standard errors clustered at the subject level. "Other Controls" refers to all variables included in Table 4. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
This table reports the linear relationship between the choice to bid using debt and average choices from the Andreoni-Harbaugh task. In the first column, the independent variable is the average proportion of the AH budget assigned to probability across all ten choices from this task. In the second column, the independent variables are the same average computed over the first five tasks (made from the 5 unique budgets) and the second five tasks (each of which is a second copy of one of the 5 unique budgets). The third column uses the Obviously Related Instrumental Variable approach from Gillen et al. (2019) in which each observation is duplicated. In half of those observations, the average choices in the first five rounds is used to instrument for the average choice in rounds 6-10, and in the other half of the observations, the reverse is carried out.

Table 19: Buyers' Security Choice by Subject Characteristics

	(1) Debt	(2) Debt	(3) Debt
CRRA ρ	-0.11*		
	(0.062)		
CRRA ρ (round 1-5)		-0.030	
		(0.057)	
CRRA ρ (round 6-10)		-0.091	
		(0.15)	
Instrumented CRRA ρ			-0.17**
			(0.082)
Other Controls	Yes	Yes	Yes
ORIV	No	No	Yes
Observations	760	760	1520

Notes: Linear regression with standard errors clustered at the subject level. "Other Controls" refers to all variables included in Table 4. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

This table reports the linear relationship between the choice to bid using debt and a nonlinear transformation of average choices from the Andreoni-Harbaugh task. In particular, as mentioned in Breig and Feldman (2024), CRRA decision makers with parameter ρ would assign the constant proportion $\frac{1-\rho}{2-\rho}$ of their budget on increasing the prize chosen. Thus, labeling the average Andreoni-Harbaugh choice as $\bar{AH}$, one estimate of ρ is $\frac{1-2\bar{AH}}{1-\bar{AH}}$. This estimate is the independent variable included in the first column. The second column uses the same procedure to estimate two values of ρ, the first from the average of the first five Andreoni-Harbaugh choices and the second from the average of rounds 6-10. Both of these estimates are then included as regressions. Finally, the third column again estimates two values of ρ in the same way as was used for the second column. We then use the Obviously Related Instrumental Variable approach from Gillen et al. (2019) in which each observation is duplicated. In half of these observations, the estimated value of ρ from the first five rounds is used to instrument for the second five rounds, while in the other half of the observations, the reverse is carried out.

Table 20: Potential Surplus

	(1) Potential Surplus	(2) Potential Surplus	(3) Potential Surplus
1PE	-40.8	-40.8	-40.8
	(67.8)	(67.7)	(67.8)
2PD	-145.3**	-145.3**	-145.3**
	(67.1)	(67.0)	(66.9)
2PE	-62.9	-62.9	-62.9
	(65.3)	(65.2)	(65.5)
Informal	-73.4	-73.4	-73.4
	(68.6)	(68.6)	(68.7)
Round		-5.69	
		(3.73)	
Constant	2682.9***	2742.7***	2714.0***
	(46.9)	(60.4)	(103.7)
Round FE	No	No	Yes
Observations	1960	1960	1960

Notes: Linear regression with robust standard errors. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
This table reports a linear regression of the potential surplus of an auction on the treatment variables. Potential surplus is defined as the maximum of the two signals of the bidders in the auction multiplied by 4000. Despite the fact that signals are drawn independently of treatment, the sample of signals drawn for the second-price debt auctions was lower than the other treatments, leading to a negative and statistically significant coefficient.

Experimental Screenshots

Below we copy screenshots of what subjects saw in the experiment.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

Thank you for participating in this study. This study is about decision-making. It should take about 120 minutes, and you will be paid based on your earnings from the experiment. The money you earn will be paid either in cash at the end of the study or electronically within a few days of the end of the study.

Please do not use any electronic devices or talk with other participants during this study.

There will be no deception in this study. Every game or decision you make will be carried out exactly as they are described in the instructions. Anything else would violate the human ethics protocol under which we run the study (UQ Human Research Ethics Approval 2021/HE000019).

The study will have two parts. In each part, you will make decisions which will affect the amount of money you earn. Part 1 of the study consists of games that you will play with other randomly selected players. The players that you are paired with in a round are independent of who you play with in any other round. In Part 2, you will make decisions individually and no other participant can affect your earnings.

If you have questions at any point, please raise your hand and we will answer your questions privately.

Next

Figure 25: Initial instructions for all formal auctions.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

Thank you for participating in this study. This study is about decision-making. It should take about 120 minutes, and you will be paid based on your earnings from the experiment. The money you earn will be paid either in cash at the end of the study or electronically within a few days of the end of the study.

Please do not use any electronic devices or talk with other participants during this study.

There will be no deception in this study. Every game or decision you make will be carried out exactly as they are described in the instructions. Anything else would violate the human ethics protocol under which we run the study (UQ Human Research Ethics Approval 2021/HE001827).

The study will have two parts. In each part, you will make decisions which will affect the amount of money you earn. Part 1 of the study consists of games that you will play with other randomly selected players. The players that you are paired with in a round are independent of who you play with in any other round. In Part 2, you will make decisions individually and no other participant can affect your earnings.

If you have questions at any point, please raise your hand and we will answer your questions privately.

Next

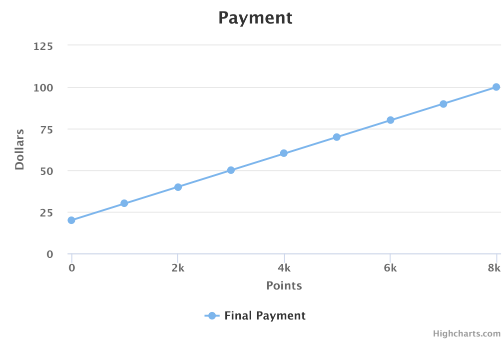
Figure 26: Initial instructions for informal auctions.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this study, you will receive points based on the choices you and other participants make. Your dollar earnings at the end of the study will depend on how many points you receive. **You will receive $20 for completing the experiment. You will be paid $2 for each question about the instructions you answer correctly. You will be paid an additional $1 for each 100 points you receive.**

At the end of the study, we will select **one** round at random to be the one that counts. Your points will be determined based on the outcome of that round. Each round is equally likely to be chosen. Because each round may be the one that counts, it is in your best interest to make each choice as if it were going to be implemented.



Important: The amount of points you receive determines how much you are paid at the end of the experiment. It is in your best interest to maximise the number of points you receive in each task.

Next

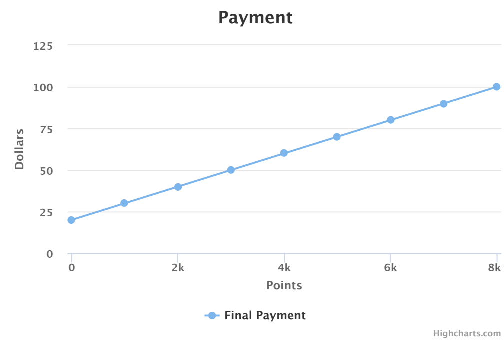
Figure 27: Payment explanation for all formal auctions.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this study, you will receive points based on the choices you and other participants make. Your dollar earnings at the end of the study will depend on how many points you receive. **You will receive $20 for completing the experiment. You will be paid $1 for each question about the instructions you answer correctly. You will be paid an additional $1 for each 100 points you receive.**

At the end of the study, we will select **one** round at random to be the one that counts. Your points will be determined based on the outcome of that round. Each round is equally likely to be chosen. Because each round may be the one that counts, it is in your best interest to make each choice as if it were going to be implemented.



Important: The amount of points you receive determines how much you are paid at the end of the experiment. It is in your best interest to maximise the number of points you receive in each task.

Next

Figure 28: Payment explanation for informal auctions.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this part of the experiment, you will participate in 20 rounds of auctions. Each auction begins with the computer randomly pairing you with another participant. The player that you are paired with in a round is selected independently of who you play with in any other round. You will not know the player you are paired with.

Before each round, you will be provided with 2000 points.

In each auction you will bid for the opportunity to make a risky investment. The cost of making the investment is the 2000 points that you are provided with at the beginning of the round. However, this investment generates revenue. The revenue of the investment is either 2000 points or 6000 points. Each bidder has a different likelihood of the investment having a revenue of 6000 points, and the likelihoods are uniformly distributed between 0 out of 100 and 100 out of 100. If you do not win the auction, you will keep the 2000 points you were initially provided with.

Important: The bids in this auction will be slightly different to auctions you may have seen before. Both players will make their bids in terms of **points** . The winner will be the player with the highest bid, and the "price" will be equal to the winner's bid. **If the revenue is higher than the price, then the winner will pay the price. If the revenue is lower than the price, then the winner pays all of the revenue.** If both players make the same bid, the winner is chosen randomly and the price is equal to their bid.

For instance, suppose that Player 1 bids 3500 while Player 2 bids 4500. Then Player 1 loses the auction and keeps the 2000 points they were provided with. Player 2 invests their 2000 points and must make a payment depending on the revenue of the investment. Because the winner's bid is higher than 2000, if the revenue is 2000 points, the winner pays 2000 points. If the revenue is instead 6000 points, the winner pays 4500 points.

The next page contains a few more examples to familiarize you with how this works. Take your time and make sure you understand how it works. After the examples, there will be a short quiz about the rules of this game. You will earn $2 for each question you answer correctly.

Next

Figure 29: Auction instructions for the first-price debt treatment

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this part of the experiment, you will participate in 20 rounds of auctions. Each auction begins with the computer randomly pairing you with another participant. The player that you are paired with in a round is selected independently of who you play with in any other round. You will not know the player you are paired with.

Before each round, you will be provided with 2000 points.

In each auction you will bid for the opportunity to make a risky investment. The cost of making the investment is the 2000 points that you are provided with at the beginning of the round. However, this investment generates revenue. The revenue of the investment is either 2000 points or 6000 points. Each bidder has a different likelihood of the investment having a revenue of 6000 points, and the likelihoods are uniformly distributed between 0 out of 100 and 100 out of 100. If you do not win the auction, you will keep the 2000 points you were initially provided with.

Important: The bids in this auction will be slightly different to auctions you may have seen before. Both players will make their bids in terms of **percentages** . The winner will be the player with the highest bid, and the "price" will be equal to the winner's bid. However, the amount the winner pays may depend on the revenue that the investment generates. **The winner pays a percentage of their revenue equal to the price.** If both players make the same bid, the winner is chosen randomly and the price is equal to their bid.

For instance, suppose that Player 1 bids 20% while Player 2 bids 45%. Then Player 1 loses the auction and keeps the 2000 points they were provided with. Player 2 invests their 2000 points, but receives (1 - 0.45) × 6000 = 3300 points if the revenue is high and (1 - 0.45) × 2000 = 1100 points if the revenue is low.

The next page contains a few more examples to familiarize you with how this works. Take your time and make sure you understand how it works. After the examples, there will be a short quiz about the rules of this game. You will earn $2 for each question you answer correctly.

Next

Figure 30: Auction instructions for the first-price equity treatment.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this part of the experiment, you will participate in 20 rounds of auctions. Each auction begins with the computer randomly pairing you with another participant. The player that you are paired with in a round is selected independently of who you play with in any other round. You will not know the player you are paired with.

Before each round, you will be provided with 2000 points.

In each auction you will bid for the opportunity to make a risky investment. The cost of making the investment is the 2000 points that you are provided with at the beginning of the round. However, this investment generates revenue. The revenue of the investment is either 2000 points or 6000 points. Each bidder has a different likelihood of the investment having a revenue of 6000 points, and the likelihoods are uniformly distributed between 0 out of 100 and 100 out of 100. If you do not win the auction, you will keep the 2000 points you were initially provided with.

Important: The bids in this auction will be slightly different to auctions you may have seen before. Both players will make their bids in terms of **points** . The winner will be the player with the highest bid, and the "price" will be equal to the loser's bid. **If the revenue is higher than the price, then the winner will pay the price. If the revenue is lower than the price, then the winner pays all of the revenue.** If both players make the same bid, the winner is chosen randomly and the price is equal to their bid.

For instance, suppose that Player 1 bids 3500 while Player 2 bids 4500. Then Player 1 loses the auction and keeps the 2000 points they were provided with. Player 2 invests their 2000 points and must make a payment depending on the revenue of the investment. Because the loser's bid is higher than 2000, if the revenue is 2000 points, the winner pays 2000 points. If the revenue is instead 6000 points, the winner pays 3500 points.

The next page contains a few more examples to familiarize you with how this works. Take your time and make sure you understand how it works. After the examples, there will be a short quiz about the rules of this game. You will earn $2 for each question you answer correctly.

Next

Figure 31: Auction instructions for the second-price debt treatment.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this part of the experiment, you will participate in 20 rounds of auctions. Each auction begins with the computer randomly pairing you with another participant. The player that you are paired with in a round is selected independently of who you play with in any other round. You will not know the player you are paired with.

Before each round, you will be provided with 2000 points.

In each auction you will bid for the opportunity to make a risky investment. The cost of making the investment is the 2000 points that you are provided with at the beginning of the round. However, this investment generates revenue. The revenue of the investment is either 2000 points or 6000 points. Each bidder has a different likelihood of the investment having a revenue of 6000 points, and the likelihoods are uniformly distributed between 0 out of 100 and 100 out of 100. If you do not win the auction, you will keep the 2000 points you were initially provided with.

Important: The bids in this auction will be slightly different to auctions you may have seen before. Both players will make their bids in terms of **percentages** . The winner will be the player with the highest bid, and the "price" will be equal to the loser's bid. However, the amount the winner pays may depend on the revenue that the investment generates. **The winner pays a percentage of their revenue equal to the price.** If both players make the same bid, the winner is chosen randomly and the price is equal to their bid.

For instance, suppose that Player 1 bids 20% while Player 2 bids 45%. Then Player 1 loses the auction and keeps the 2000 points they were provided with. Player 2 invests their 2000 points, but receives (1 - 0.2) × 6000 = 4800 points if the revenue is high and (1 - 0.2) × 2000 = 1600 points if the revenue is low.

The next page contains a few more examples to familiarize you with how this works. Take your time and make sure you understand how it works. After the examples, there will be a short quiz about the rules of this game. You will earn $2 for each question you answer correctly.

Next

Figure 32: Auction instructions for the second-price equity treatment.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this part of the experiment, you will participate in 20 rounds of auctions. Each auction begins with the computer randomly pairing you with another two participants. The players that you are paired with in a round are selected independently of who you play with in any other round. You will not know the players you are paired with. Each auction stands alone — your choices in one round do not affect the outcome of subsequent rounds.

You will be randomly assigned the role of either a bidder or a seller at the start of the experiment. You will remain in this role throughout the experiment.

Before each auction, players who are bidders will be provided with 2000 points.

In each auction, bidders will bid for the opportunity to make a risky investment. The cost of making the investment is the 2000 points that bidders are provided with before each auction. This investment generates revenue. The revenue from the investment is either 2000 points or 6000 points. Each bidder has a different likelihood of the investment having a revenue of 6000 points, and **the likelihoods are uniformly distributed between 0% and 100%**. If you do not win the auction, you will keep the 2000 points you were initially provided with, and this will be your payoff for the round.

Important: The bids in this auction will be slightly different to auctions you may have seen before. Bidders will make their bids in terms of **equity percentages** or **debt payments**. The winning bid of each auction will be chosen by the player acting as the seller. The "price" will be equal to the winner's bid.

The amount the winner pays and seller receives may depend on the bid type and revenue that the investment generates.

The bidder chooses whether to submit a debt or equity bid.

Equity Bids: If the winner bids with equity, the winner **pays a percentage of their revenue equal to the price** (their bid). The bidder receives either (1 - Bid %) × 6000 or (1 - Bid %) × 2000 points as their payoff. The seller receives either (Bid %) × 6000 or (Bid %) × 2000 points as their payoff.

Debt Bids: If the winner bids with debt, the winner **pays a fixed amount of revenue equal to the price** (their bid) before receiving any revenue earned over their bid. Thus, the bidder either receives (6000 - Bid) or (2000 - Bid) points as their payoff. The bidder cannot receive less than 0 points. The seller receives the price as their guaranteed payoff.

In each auction, the seller will choose which bid is the winner.

The next page contains examples to familiarize you with how this works. Take your time and make sure you understand how it works. We will not begin until everybody completes these examples.

Very Important: For each auction, the sliders are tools to help you decide the bid you like the best. Therefore, it is in your best interest to move them around to help you determine which bid you like better.

Next

Figure 33: Auction instructions for the informal treatment.

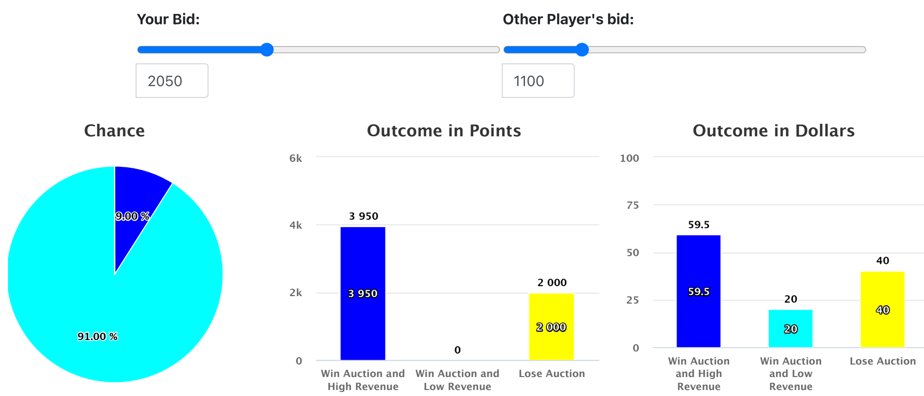
Examples

Example 1: Alice and Bob participate in this type of auction. Alice finds out that her project has a 53% chance of generating a high revenue, while Bob finds out that his project has an 81% chance of generating the high revenue.
Alice bids 1000 points and Bob bids 1800 points. Then Alice loses the auction and is guaranteed a payoff of 2000 points.
Bob wins the auction and has an 81% chance of receiving 6000 - 1800 = 4200 points and a 19% chance of receiving 2000 - 1800 = 200 points.

Example 2: Carmen and Daron participate in this type of auction. Carmen finds out that her project has a 42% chance of generating a high revenue, while Daron finds out that his project has an 55% chance of generating the high revenue.
Carmen bids 2400 points and Daron bids 2200 points. Then Daron loses the auction and is guaranteed a payoff of 2000 points.
Carmen wins the auction and has a 42% chance of receiving 6000 - 2400 = 3600 points, but because Carmen's bid is higher than 2000, Carmen has a 58% chance of receiving 0 points.

Compare bids: The interactive figure below will help show you what your payoffs will be conditional on your and your and the other player's bids. Once you move a slider, the diagram will show you the likelihood of winning the auction with high revenue, the likelihood of winning the auction with low revenue, and the likelihood of losing the auction. It will also show you the number of points and the final dollar outcomes associated with each of these outcomes. Try out different bids to make sure you understand the consequences of your choices.

For instance, suppose that if you win, the likelihood that the project's revenue will be 6000 is 9%. That means that the likelihood that the project's revenue will be 2000 is 91%.



When you are ready to continue, press next and you will begin the quiz.

Next

Figure 34: Examples for the first-price debt treatment.

Examples

Example 1: Alice and Bob participate in this type of auction. Alice finds out that her project has a 53% chance of generating a high revenue, while Bob finds out that his project has an 81% chance of generating the high revenue.
Alice bids 30% and Bob bids 43%. Then Alice loses the auction and is guaranteed a payoff of 2000 points.
Bob wins the auction and has an 81% chance of receiving (1 - 0.43) × 6000 = 3420 points and a 19% chance of receiving (1 - 0.43) × 2000 = 1140 points.

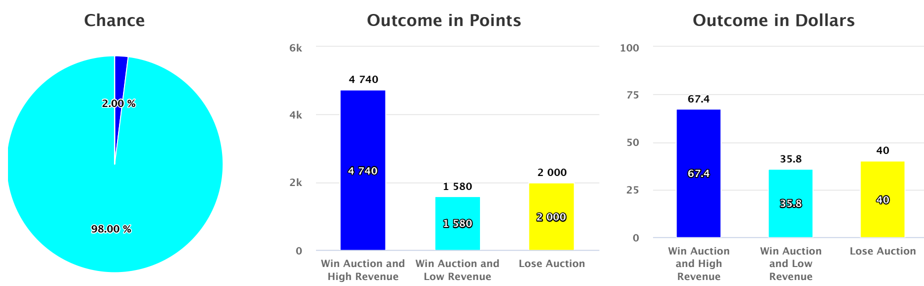
Example 2: Carmen and Daron participate in this type of auction. Carmen finds out that her project has a 42% chance of generating a high revenue, while Daron finds out that his project has an 55% chance of generating the high revenue.
Carmen bids 27% and Daron bids 22%. Then Daron loses the auction and is guaranteed a payoff of 2000 points.
Carmen wins the auction and has a 42% chance of receiving (1 - 0.27) × 6000 = 4380 points and a 58% chance of receiving (1 - 0.27) × 2000 = 1460 points.

Compare bids: The interactive figure below will help show you what your payoffs will be conditional on your and your and the other player's bids. Once you move a slider, the diagram will show you the likelihood of winning the auction with high revenue, the likelihood of winning the auction with low revenue, and the likelihood of losing the auction. It will also show you the number of points and the final dollar outcomes associated with each of these outcomes. Try out different bids to make sure you understand the consequences of your choices.

For instance, suppose that if you win, the likelihood that the project's revenue will be 6000 is 2%. That means that the likelihood that the project's revenue will be 2000 is 98%.

Your Bid: 21

Other Player's bid: 16



When you are ready to continue, press next and you will begin the quiz.

Next

Figure 35: Examples for the first-price equity treatment.

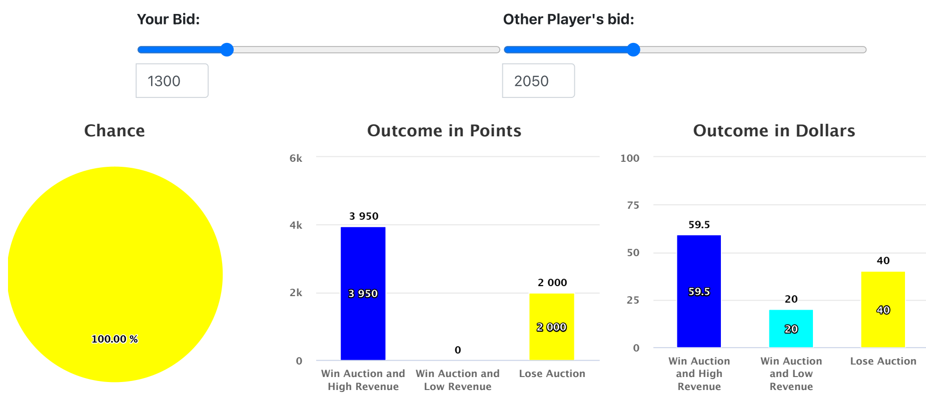
Examples

Example 1: Alice and Bob participate in this type of auction. Alice finds out that her project has a 53% chance of generating a high revenue, while Bob finds out that his project has an 81% chance of generating the high revenue.
Alice bids 1000 points and Bob bids 1800 points. Then Alice loses the auction and is guaranteed a payoff of 2000 points.
Bob wins the auction and has an 81% chance of receiving 6000 - 1000 = 5000 points and a 19% chance of receiving 2000 - 1000 = 1000 points.

Example 2: Carmen and Daron participate in this type of auction. Carmen finds out that her project has a 42% chance of generating a high revenue, while Daron finds out that his project has an 55% chance of generating the high revenue.
Carmen bids 2400 points and Daron bids 2200 points. Then Daron loses the auction and is guaranteed a payoff of 2000 points.
Carmen wins the auction and has a 42% chance of receiving 6000 - 2200 = 3800 points, but because Daron's bid is higher than 2000, Carmen has a 58% chance of receiving 0 points.

Compare bids: The interactive figure below will help show you what your payoffs will be conditional on your and your and the other player's bids. Once you move a slider, the diagram will show you the likelihood of winning the auction with high revenue, the likelihood of winning the auction with low revenue, and the likelihood of losing the auction. It will also show you the number of points and the final dollar outcomes associated with each of these outcomes. Try out different bids to make sure you understand the consequences of your choices.

For instance, suppose that if you win, the likelihood that the project's revenue will be 6000 is 74%. That means that the likelihood that the project's revenue will be 2000 is 26%.



When you are ready to continue, press next and you will begin the quiz.

Next

Figure 36: Examples for the second-price debt treatment.

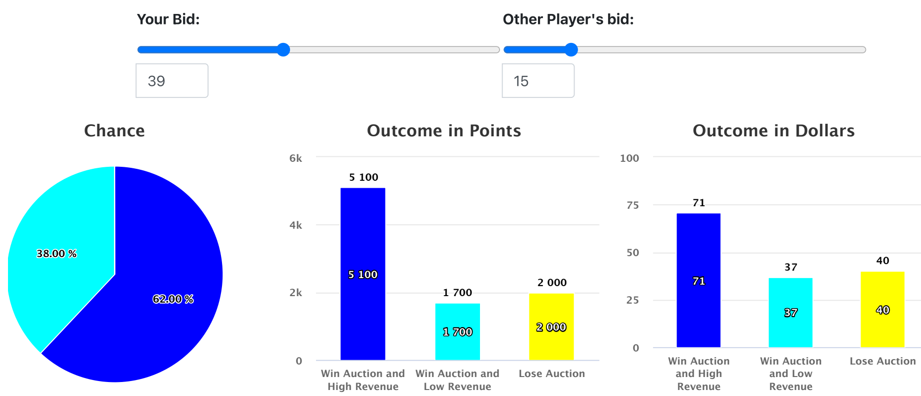
Examples

Example 1: Alice and Bob participate in this type of auction. Alice finds out that her project has a 53% chance of generating a high revenue, while Bob finds out that his project has an 81% chance of generating the high revenue.
Alice bids 30% and Bob bids 43%. Then Alice loses the auction and is guaranteed a payoff of 2000 points.
Bob wins the auction and has an 81% chance of receiving (1 - 0.3) × 4200 = 3420 points and a 19% chance of receiving (1 - 0.3) × 2000 = 1400 points.

Example 2: Carmen and Daron participate in this type of auction. Carmen finds out that her project has a 42% chance of generating a high revenue, while Daron finds out that his project has an 55% chance of generating the high revenue.
Carmen bids 27% and Daron bids 22%. Then Daron loses the auction and is guaranteed a payoff of 2000 points.
Carmen wins the auction and has a 42% chance of receiving (1 - 0.22) × 6000 = 4680 points and a 58% chance of receiving (1 - 0.22) × 2000 = 1560 points.

Compare bids: The interactive figure below will help show you what your payoffs will be conditional on your and your and the other player's bids. Once you move a slider, the diagram will show you the likelihood of winning the auction with high revenue, the likelihood of winning the auction with low revenue, and the likelihood of losing the auction. It will also show you the number of points and the final dollar outcomes associated with each of these outcomes. Try out different bids to make sure you understand the consequences of your choices.

For instance, suppose that if you win, the likelihood that the project's revenue will be 6000 is 62%. That means that the likelihood that the project's revenue will be 2000 is 38%.



When you are ready to continue, press next and you will begin the quiz.

Next

Figure 37: Examples for the second-price equity treatment.

Examples

Example 1: Aditya, Bridget, and Callum participate in this type of auction. Aditya and Bridget are bidders, and Callum is a seller. Aditya finds out that his project has a 53% chance of generating the high revenue, while Bridget finds out that her project has an 81% chance of generating the high revenue. Both bid with equity. Aditya bids 27% and Bridget bids 30%. The seller (Callum) then chooses the winner without knowing the high revenue chances of each of the bidders.

In this example, we will say that Callum chooses Bridget as the winner. Aditya loses the auction and is guaranteed a payoff of 2000 points. Bridget wins the auction and has an 81% chance of receiving (1 - 0.3) × 6000 = 4200 points and a 19% chance of receiving (1 - 0.3) × 2000 = 1400 points. This means that Callum has an 81% chance of receiving 0.3 × 6000 = 1800 points and a 19% chance of receiving 0.3 × 2000 = 600 points.

Example 2: Declan, Edward, and George participate in this type of auction. Declan finds out that his project has a 42% chance of generating the high revenue, while Edward finds out that his project has a 55% chance of generating the high revenue. Both bid with debt. Declan bids 1800 points and Edward bids 1500 points. The seller (George) then chooses the winner without knowing the high revenue chances of each of the bidders.

In this example, we will say that George chooses Declan as the winner. Edward loses the auction and is guaranteed a payoff of 2000 points. Declan wins the auction and has a 42% chance of receiving 6000 - 1800 = 4200 points and a 58% chance of receiving 2000 - 1800 = 200 points. Players cannot receive negative points. As George has selected a debt bid as the winner, he is guaranteed to receive 1800 points as his payoff.

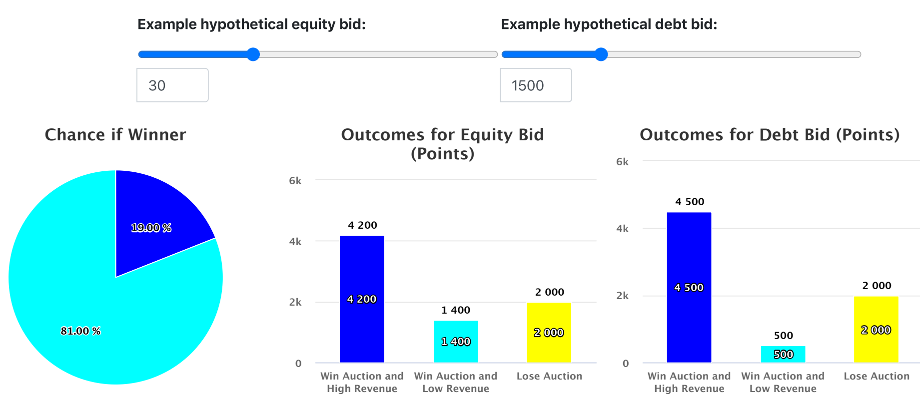
Example 3: Maja, Nicole, and Tom participate in this type of auction. Maja finds out that her project has a 40% chance of generating the high revenue, while Nicole finds out that her project has a 50% chance of generating the high revenue. Maja makes an equity bid of 45%, and Nicole makes a debt bid of 1800. The seller (Tom) then chooses the winner without knowing the high revenue chances of each of the bidders.

Tom's preferences will determine his choice between a debt and equity bid. If Tom chooses Maja as the winner, he has a 40% chance of receiving 0.45 × 6000 = 2700 points and a 60% chance of receiving 0.45 × 2000 = 900 points. If Tom chooses Nicole as the winner, he will receive a guaranteed 1800 points.

Important: In every auction, the seller does not know the percentage chances of the bidders' revenue being high or low.

Try it out: For each auction, players will be given an interactive figure that will help show what their payoffs will be, conditional on their choices. Below are the diagrams displayed to bidders in each auction. Once you move a slider, the diagram will show you the likelihood of winning the auction with high revenue, and the likelihood of winning the auction with low revenue. It will also show you the number of points you stand to receive under a debt or equity bid of different values. Try out different bids below to make sure you understand the consequences of your choices.

For instance, suppose that if you win, the likelihood that the project's revenue will be 6000 is 19%. That means that the likelihood that the project's revenue will be 2000 is 81%.



When you are ready to continue, press next to answer some questions to test your understanding.

Next

Figure 38: Examples for the informal treatment.

Quiz

You will now be given a series of questions to check your understanding of the instructions and examples. You will be paid $2 for each answer you get correct.

How is the auction winner decided?

- ○ Another player chooses the winner.
- ○ The computer randomly chooses the winner from all bidders.
- ◉ The computer randomly chooses the winner from the highest bidders.

What will each player know about the chance of high revenue?

- ◉ Each player only knows their own chance.
- ○ Each player knows their chance and the other player's chance.
- ○ Each player knows their chance and learns the other player's chance after the auction.
- ○ Neither player knows either player's chance.

How will the auction's price be set?

- ◉ The price is equal to the highest bid.
- ○ The price is equal to the second highest bid.
- ○ The price is randomly selected from the two bids.
- ○ The price is a randomly selected value between the two bids.

How is the price used when computing payoffs?

- ○ The auction's winner pays either the price or their revenue, whichever is smaller.
- ◉ The auction's winner receives either the price or their revenue, whichever is smaller.
- ○ The auction's loser pays either the price or their revenue, whichever is smaller.
- ○ The auction's loser receives either the price or their revenue, whichever is smaller.

Suppose that the other player bids 1000 points and you bid 500 points. How many points will each player receive?

- ○ You will receive 2000 points. The other player will receive 1000 points if the revenue is low and 5000 points if the revenue is high.
- ◉ You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.
- ○ You will receive 1000 points if the revenue is low and 5000 points if the revenue is high. The other player will receive 2000 points.
- ○ You will receive 1500 points if the revenue is low and 5500 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 1000 points and you bid 5500 points. How many points will each player receive?

- ◉ You will receive 2000 points. The other player will receive 1000 points if the revenue is low and 5000 points if the revenue is high.
- ○ You will receive 2000 points. The other player will receive 0 points if the revenue is low and 500 points if the revenue is high.
- ○ You will receive 1000 points if the revenue is low and 5000 points if the revenue is high. The other player will receive 2000 points.
- ○ You will receive 0 points if the revenue is low and 500 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 4500 points and you bid 500 points. How many points will each player receive?

- ○ You will receive 2000 points. The other player will receive 0 points if the revenue is low and 1500 points if the revenue is high.
- ○ You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.

Figure 39: Quiz for the first-price debt treatment.

- (selected) You will receive 0 points if the revenue is low and 1500 points if the revenue is high. The other player will receive 2000 points.
- You will receive 1500 points if the revenue is low and 5500 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 4500 and you bid 5500 points. How many points will each player receive?

- (selected) You will receive 2000 points. The other player will receive 0 points if the revenue is low and 1500 points if the revenue is high.
- You will receive 2000 points. The other player will receive 0 points if the revenue is low and 500 points if the revenue is high.
- You will receive 0 points if the revenue is low and 1500 points if the revenue is high. The other player will receive 2000 points.
- You will receive 0 points if the revenue is low and 500 points if the revenue is high. The other player will receive 2000 points.

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

Next

Figure 40: Quiz for the first-price debt treatment.

Quiz

You will now be given a series of questions to check your understanding of the instructions and examples. You will be paid $2 for each answer you get correct.

How is the auction winner decided?

- Another player chooses the winner.
- The computer randomly chooses the winner from all bidders.
- The computer randomly chooses the winner from the highest bidders.

What will each player know about the chance of high revenue?

- Each player only knows their own chance.
- Each player knows their chance and the other player's chance.
- Each player knows their chance and learns the other player's chance after the auction.
- Neither player knows either player's chance.

How will the auction's price be set?

- The price is equal to the highest bid.
- The price is equal to the second highest bid.
- The price is randomly selected from the two bids.
- The price is a randomly selected value between the two bids.

How is the price used when computing payoffs?

- The auction's winner pays a percentage of their revenue equal to the price.
- The auction's winner receives a percentage of their revenue equal to the price.
- The auction's loser pays a percentage of their revenue equal to the price
- The auction's loser receives a percentage of their revenue equal to the price.

Suppose that the other player bids 20% and you bid 10%. How many points will each player receive?

- You will receive 2000 points. The other player will receive 1600 points if the revenue is low and 4800 points if the revenue is high.
- You will receive 2000 points. The other player will receive 1800 points if the revenue is low and 5400 points if the revenue is high.
- You will receive 1600 points if the revenue is low and 4800 points if the revenue is high. The other player will receive 2000 points.
- You will receive 1800 points if the revenue is low and 5400 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 20% and you bid 80%. How many points will each player receive?

- You will receive 2000 points. The other player will receive 1600 points if the revenue is low and 4800 points if the revenue is high.
- You will receive 2000 points. The other player will receive 400 points if the revenue is low and 1200 points if the revenue is high.
- You will receive 1600 points if the revenue is low and 4800 points if the revenue is high. The other player will receive 2000 points.
- You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 70% and you bid 10%. How many points will each player receive?

- You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.
- You will receive 2000 points. The other player will receive 1800 points if the revenue is low and 5400 points if the revenue is high.

Figure 41: Quiz for the first-price equity treatment.

- You will receive 600 points if the revenue is low and 1800 points if the revenue is high. The other player will receive 2000 points.
- You will receive 1800 points if the revenue is low and 5400 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 70% and you bid 80%. How many points will each player receive?

- You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.
- You will receive 2000 points. The other player will receive 400 points if the revenue is low and 1200 points if the revenue is high.
- You will receive 600 points if the revenue is low and 1800 points if the revenue is high. The other player will receive 2000 points.
- You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.

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

Next

Figure 42: Quiz for the first-price equity treatment.

Quiz

You will now be given a series of questions to check your understanding of the instructions and examples. You will be paid $2 for each answer you get correct.

How is the auction winner decided?

- ○ Another player chooses the winner.
- ○ The computer randomly chooses the winner from all bidders.
- ◉ The computer randomly chooses the winner from the highest bidders.

What will each player know about the chance of high revenue?

- ○ Each player only knows their own chance.
- ○ Each player knows their chance and the other player's chance.
- ◉ Each player knows their chance and learns the other player's chance after the auction.
- ○ Neither player knows either player's chance.

How will the auction's price be set?

- ○ The price is equal to the highest bid.
- ◉ The price is equal to the second highest bid.
- ○ The price is randomly selected from the two bids.
- ○ The price is a randomly selected value between the two bids.

How is the price used when computing payoffs?

- ○ The auction's winner pays either the price or their revenue, whichever is smaller.
- ◉ The auction's winner receives either the price or their revenue, whichever is smaller.
- ○ The auction's loser pays either the price or their revenue, whichever is smaller.
- ○ The auction's loser receives either the price or their revenue, whichever is smaller.

Suppose that the other player bids 1000 points and you bid 500 points. How many points will each player receive?

- ○ You will receive 2000 points. The other player will receive 1000 points if the revenue is low and 5000 points if the revenue is high.
- ◉ You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.
- ○ You will receive 1000 points if the revenue is low and 5000 points if the revenue is high. The other player will receive 2000 points.
- ○ You will receive 1500 points if the revenue is low and 5500 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 1000 points and you bid 5500 points. How many points will each player receive?

- ○ You will receive 2000 points. The other player will receive 1000 points if the revenue is low and 5000 points if the revenue is high.
- ◉ You will receive 2000 points. The other player will receive 0 points if the revenue is low and 500 points if the revenue is high.
- ○ You will receive 1000 points if the revenue is low and 5000 points if the revenue is high. The other player will receive 2000 points.
- ○ You will receive 0 points if the revenue is low and 500 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 4500 points and you bid 500 points. How many points will each player receive?

- ○ You will receive 2000 points. The other player will receive 0 points if the revenue is low and 1500 points if the revenue is high.
- ◉ You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.

Figure 43: Quiz for the second-price debt treatment.

- You will receive 0 points if the revenue is low and 1500 points if the revenue is high. The other player will receive 2000 points.
- You will receive 1500 points if the revenue is low and 5500 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 4500 and you bid 5500 points. How many points will each player receive?

- You will receive 2000 points. The other player will receive 0 points if the revenue is low and 1500 points if the revenue is high.
- You will receive 2000 points. The other player will receive 0 points if the revenue is low and 500 points if the revenue is high.
- You will receive 0 points if the revenue is low and 1500 points if the revenue is high. The other player will receive 2000 points.
- You will receive 0 points if the revenue is low and 500 points if the revenue is high. The other player will receive 2000 points.

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

Next

Figure 44: Quiz for the second-price debt treatment.

Quiz

You will now be given a series of questions to check your understanding of the instructions and examples. You will be paid $2 for each answer you get correct.

How is the auction winner decided?

- [ ] Another player chooses the winner.
- [ ] The computer randomly chooses the winner from all bidders.
- [x] The computer randomly chooses the winner from the highest bidders.

What will each player know about the chance of high revenue?

- [x] Each player only knows their own chance.
- [ ] Each player knows their chance and the other player's chance.
- [ ] Each player knows their chance and learns the other player's chance after the auction.
- [ ] Neither player knows either player's chance.

How will the auction's price be set?

- [x] The price is equal to the highest bid.
- [ ] The price is equal to the second highest bid.
- [ ] The price is randomly selected from the two bids.
- [ ] The price is a randomly selected value between the two bids.

How is the price used when computing payoffs?

- [ ] The auction's winner pays a percentage of their revenue equal to the price.
- [ ] The auction's winner receives a percentage of their revenue equal to the price.
- [x] The auction's loser pays a percentage of their revenue equal to the price
- [ ] The auction's loser receives a percentage of their revenue equal to the price.

Suppose that the other player bids 20% and you bid 10%. How many points will each player receive?

- [ ] You will receive 2000 points. The other player will receive 1600 points if the revenue is low and 4800 points if the revenue is high.
- [ ] You will receive 2000 points. The other player will receive 1800 points if the revenue is low and 5400 points if the revenue is high.
- [x] You will receive 1600 points if the revenue is low and 4800 points if the revenue is high. The other player will receive 2000 points.
- [ ] You will receive 1800 points if the revenue is low and 5400 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 20% and you bid 80%. How many points will each player receive?

- [x] You will receive 2000 points. The other player will receive 1600 points if the revenue is low and 4800 points if the revenue is high.
- [ ] You will receive 2000 points. The other player will receive 400 points if the revenue is low and 1200 points if the revenue is high.
- [ ] You will receive 1600 points if the revenue is low and 4800 points if the revenue is high. The other player will receive 2000 points.
- [ ] You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 70% and you bid 10%. How many points will each player receive?

- [x] You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.
- [ ] You will receive 2000 points. The other player will receive 1800 points if the revenue is low and 5400 points if the revenue is high.

Figure 45: Quiz for the second-price equity treatment.

- ○ You will receive 600 points if the revenue is low and 1800 points if the revenue is high. The other player will receive 2000 points.
- ○ You will receive 1800 points if the revenue is low and 5400 points if the revenue is high. The other player will receive 2000 points.

Suppose that the other player bids 70% and you bid 80%. How many points will each player receive?

- ○ You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.
- ○ You will receive 2000 points. The other player will receive 400 points if the revenue is low and 1200 points if the revenue is high.
- ○ You will receive 600 points if the revenue is low and 1800 points if the revenue is high. The other player will receive 2000 points.
- ◉ You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.

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

Next

Figure 46: Quiz for the second-price equity treatment.

Quiz

You will now be given a series of questions to check your understanding of the instructions and examples. You will be paid $1.00 for each answer you get correct.

How is the auction winner decided?

- ○ The seller chooses the winner
- ○ The computer randomly chooses the winner
- ○ The highest equity bid always wins
- ○ The highest debt bid always wins

Which of the following best describes a winning EQUITY bid?

- ○ The first 30% of the revenue earned (either 1800 or 600 points) goes to the seller, the rest is kept by the buyer
- ○ The first 1800 points of the revenue earned goes to the seller, the rest is kept by the buyer

Which of the following best describes a winning DEBT bid?

- ○ The first 30% of the revenue earned (either 1800 or 600 points) goes to the seller, the rest is kept by the buyer
- ○ The first 1800 points of the revenue earned goes to the seller, the rest is kept by the buyer

Are the chances of earning the high revenue the same for both bidders?

- ○ Yes
- ○ No

Does the seller know the chances of bidders earning the high revenue?

- ○ Yes
- ○ No

What happens for the bidder that loses the auction?

- ○ They keep their endowment of 2000 points, this becomes their payoff
- ○ They lose their endowment of 2000 points, and receive no payoff
- ○ They receive the same payoff as the seller
- ○ They receive the same payoff as the winner

Example A: An equity bid of 25% wins the auction. What are the winning bidder's payoffs in the high (6000) and low (2000) revenue states?

- ○ High = 1500 and Low = 500
- ○ High = 4500 and Low = 1500
- ○ High = 6000 and Low = 2000
- ○ High = 3000 and Low = 1000

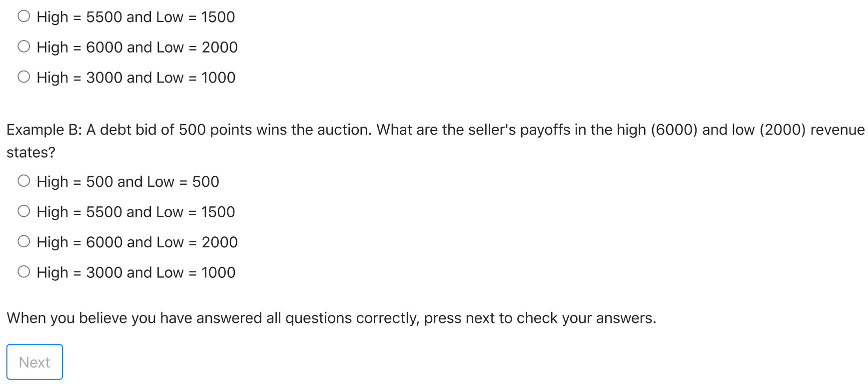
Example A: An equity bid of 25% wins the auction. What are the seller's payoffs in the high (6000) and low (2000) revenue states?

- ○ High = 1500 and Low = 500
- ○ High = 4500 and Low = 1500
- ○ High = 6000 and Low = 2000
- ○ High = 3000 and Low = 1000

Example B: A debt bid of 500 points wins the auction. What are the winning bidder's payoffs in the high (6000) and low (2000) revenue states?

- ○ High = 500 and Low = 500

Figure 47: Quiz for the informal treatment.



- ○ High = 5500 and Low = 1500
- ○ High = 6000 and Low = 2000
- ○ High = 3000 and Low = 1000

Example B: A debt bid of 500 points wins the auction. What are the seller's payoffs in the high (6000) and low (2000) revenue states?

- ○ High = 500 and Low = 500
- ○ High = 5500 and Low = 1500
- ○ High = 6000 and Low = 2000
- ○ High = 3000 and Low = 1000

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

Next

Figure 48: Quiz for the informal treatment.

Quiz Answers

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

Question 1: How is the auction winner decided?
Correct Answer: The computer randomly chooses the winner from the highest bidders.
Your Answer: The computer randomly chooses the winner from the highest bidders.

Question 2: What will each player know about the chance of high revenue?
Correct Answer: Each player only knows their own chance.
Your Answer: Each player only knows their own chance.

Question 3: How will the auction's price be set?
Correct Answer: The price is equal to the highest bid.
Your Answer: The price is equal to the highest bid.

Question 4: How is the price used when computing payoffs?
Correct Answer: The auction's winner pays either the price or their revenue, whichever is smaller.
Your Answer: The auction's winner receives either the price or their revenue, whichever is smaller.

Question 5: Suppose that the other player bids 1000 points and you bid 500 points. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 1000 points if the revenue is low and 5000 points if the revenue is high.
Your Answer: You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.

Question 6: Suppose that the other player bids 1000 points and you bid 5500 points. How many points will each player receive?
Correct Answer: You will receive 0 points if the revenue is low and 500 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 2000 points. The other player will receive 1000 points if the revenue is low and 5000 points if the revenue is high.

Question 7: Suppose that the other player bids 4500 points and you bid 500 points. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 0 points if the revenue is low and 1500 points if the revenue is high.
Your Answer: You will receive 0 points if the revenue is low and 1500 points if the revenue is high. The other player will receive 2000 points.

Question 8: Suppose that the other player bids 4500 and you bid 5500 points. How many points will each player receive?
Correct Answer: You will receive 0 points if the revenue is low and 500 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 2000 points. The other player will receive 0 points if the revenue is low and 1500 points if the revenue is high.

You earned $6.0 from your correct answers. Please review any questions you answered incorrectly. When you are ready to begin the auction, click the next button.

Next

Figure 49: Quiz answers for the first-price debt treatment.

Quiz Answers

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

Question 1: How is the auction winner decided?
Correct Answer: The computer randomly chooses the winner from the highest bidders.
Your Answer: The computer randomly chooses the winner from the highest bidders.

Question 2: What will each player know about the chance of high revenue?
Correct Answer: Each player only knows their own chance.
Your Answer: Each player only knows their own chance.

Question 3: How will the auction's price be set?
Correct Answer: The price is equal to the highest bid.
Your Answer: The price is equal to the second highest bid.

Question 4: How is the price used when computing payoffs?
Correct Answer: The auction's winner pays a percentage of their revenue equal to the price.
Your Answer: The auction's loser pays a percentage of their revenue equal to the price

Question 5: Suppose that the other player bids 20% and you bid 10%. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 1600 points if the revenue is low and 4800 points if the revenue is high.
Your Answer: You will receive 2000 points. The other player will receive 1600 points if the revenue is low and 4800 points if the revenue is high.

Question 6: Suppose that the other player bids 20% and you bid 80%. How many points will each player receive?
Correct Answer: You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.

Question 7: Suppose that the other player bids 70% and you bid 10%. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.
Your Answer: You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.

Question 8: Suppose that the other player bids 70% and you bid 80%. How many points will each player receive?
Correct Answer: You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.

You earned $10.0 from your correct answers. Please review any questions you answered incorrectly. When you are ready to begin the auction, click the next button.

Next

Figure 50: Quiz answers for the first-price equity treatment.

Quiz Answers

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

Question 1: How is the auction winner decided?
Correct Answer: The computer randomly chooses the winner from the highest bidders.
Your Answer: The computer randomly chooses the winner from the highest bidders.

Question 2: What will each player know about the chance of high revenue?
Correct Answer: Each player only knows their own chance.
Your Answer: Each player knows their chance and learns the other player's chance after the auction.

Question 3: How will the auction's price be set?
Correct Answer: The price is equal to the second highest bid.
Your Answer: The price is equal to the second highest bid.

Question 4: How is the price used when computing payoffs?
Correct Answer: The auction's winner pays either the price or their revenue, whichever is smaller.
Your Answer: The auction's winner receives either the price or their revenue, whichever is smaller.

Question 5: Suppose that the other player bids 1000 points and you bid 500 points. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.
Your Answer: You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.

Question 6: Suppose that the other player bids 1000 points and you bid 5500 points. How many points will each player receive?
Correct Answer: You will receive 1000 points if the revenue is low and 5000 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 2000 points. The other player will receive 0 points if the revenue is low and 500 points if the revenue is high.

Question 7: Suppose that the other player bids 4500 points and you bid 500 points. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.
Your Answer: You will receive 2000 points. The other player will receive 1500 points if the revenue is low and 5500 points if the revenue is high.

Question 8: Suppose that the other player bids 4500 and you bid 5500 points. How many points will each player receive?
Correct Answer: You will receive 0 points if the revenue is low and 1500 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 2000 points. The other player will receive 0 points if the revenue is low and 500 points if the revenue is high.

You earned $8.0 from your correct answers. Please review any questions you answered incorrectly. When you are ready to begin the auction, click the next button.

Next

Figure 51: Quiz answers for the second-price debt treatment.

Quiz Answers

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

Question 1: How is the auction winner decided?
Correct Answer: The computer randomly chooses the winner from the highest bidders.
Your Answer: The computer randomly chooses the winner from the highest bidders.

Question 2: What will each player know about the chance of high revenue?
Correct Answer: Each player only knows their own chance.
Your Answer: Each player only knows their own chance.

Question 3: How will the auction's price be set?
Correct Answer: The price is equal to the second highest bid.
Your Answer: The price is equal to the highest bid.

Question 4: How is the price used when computing payoffs?
Correct Answer: The auction's winner pays a percentage of their revenue equal to the price.
Your Answer: The auction's loser pays a percentage of their revenue equal to the price

Question 5: Suppose that the other player bids 20% and you bid 10%. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 1800 points if the revenue is low and 5400 points if the revenue is high.
Your Answer: You will receive 1600 points if the revenue is low and 4800 points if the revenue is high. The other player will receive 2000 points.

Question 6: Suppose that the other player bids 20% and you bid 80%. How many points will each player receive?
Correct Answer: You will receive 1600 points if the revenue is low and 4800 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 2000 points. The other player will receive 1600 points if the revenue is low and 4800 points if the revenue is high.

Question 7: Suppose that the other player bids 70% and you bid 10%. How many points will each player receive?
Correct Answer: You will receive 2000 points. The other player will receive 1800 points if the revenue is low and 5400 points if the revenue is high.
Your Answer: You will receive 2000 points. The other player will receive 600 points if the revenue is low and 1800 points if the revenue is high.

Question 8: Suppose that the other player bids 70% and you bid 80%. How many points will each player receive?
Correct Answer: You will receive 600 points if the revenue is low and 1800 points if the revenue is high. The other player will receive 2000 points.
Your Answer: You will receive 400 points if the revenue is low and 1200 points if the revenue is high. The other player will receive 2000 points.

You earned $4.0 from your correct answers. Please review any questions you answered incorrectly. When you are ready to begin the auction, click the next button.

Next

Figure 52: Quiz answers for the second-price equity treatment.

Quiz Answers

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

Question 1: How is the auction winner decided?
Correct Answer: The seller chooses the winner.
Your Answer: The seller chooses the winner.

Question 2: Which of the following best describes a winning EQUITY bid?
Correct Answer: The first 30% of the revenue earned (either 1800 or 600 points) goes to the seller, the rest is kept by the buyer.
Your Answer: The first 30% of the revenue earned (either 1800 or 600 points) goes to the seller, the rest is kept by the buyer.

Question 3: Which of the following best describes a winning DEBT bid?
Correct Answer: The first 1800 points of the revenue earned goes to the seller, the rest is kept by the buyer
Your Answer: The first 30% of the revenue earned (either 1800 or 600 points) goes to the seller, the rest is kept by the buyer.

Question 4: Are the chances of earning the high revenue the same for both bidders?
Correct Answer: No.
Your Answer: Yes.

Question 5: Does the seller know the chances of bidders earning the high revenue?
Correct Answer: No.
Your Answer: Yes.

Question 6: "What happens for the bidder that loses the auction?
Correct Answer: They keep their endowment of 2000 points, this becomes their payoff.
Your Answer: They keep their endowment of 2000 points, this becomes their payoff.

Question 7: Example A: An equity bid of 25% wins the auction. What are the winning bidder's payoffs in the high (6000) and low (2000) revenue states?
Correct Answer: High = 4500 and Low = 1500
Your Answer: High = 1500 and Low = 500.

Question 8: Example A: An equity bid of 25% wins the auction. What are the seller's payoffs in the high (6000) and low (2000) revenue states?
Correct Answer: High = 1500 and Low = 500
Your Answer: High = 1500 and Low = 500.

Question 9: Example B: A debt bid of 500 points wins the auction. What are the winning bidder's payoffs in the high (6000) and low (2000) revenue states?
Correct Answer: High = 5500 and Low = 1500
Your Answer: High = 500 and Low = 500.

Question 10: Example B: A debt bid of 500 points wins the auction. What are the seller's payoffs in the high (6000) and low (2000) revenue states?
Correct Answer: High = 500 and Low = 500
Your Answer: High = 500 and Low = 500.

You answered 5 questions correctly, and received $5.0.
Please review any questions you answered incorrectly. When you are ready to begin the auction, click the next button.

Next

Figure 53: Quiz answers for the informal treatment.

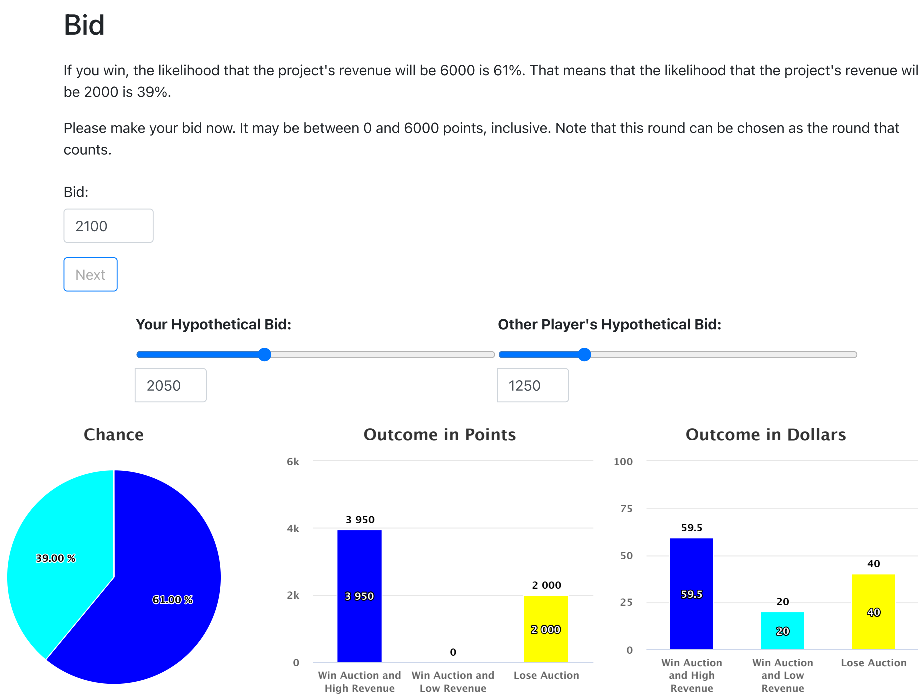


Figure 54: Bidding page for the first-price debt treatment.

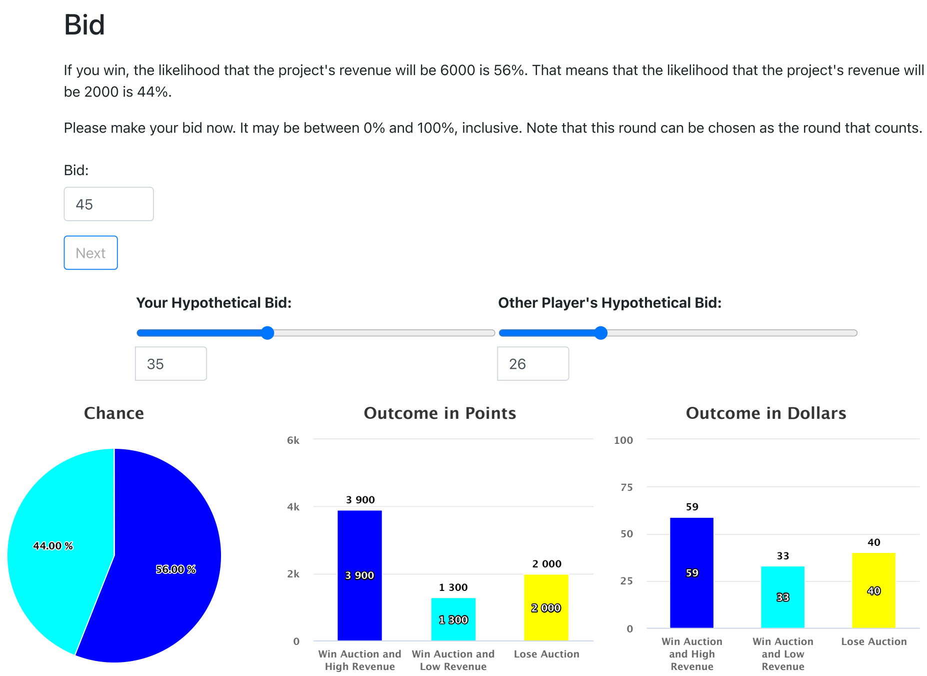


Figure 55: Bidding page for the first-price equity treatment.

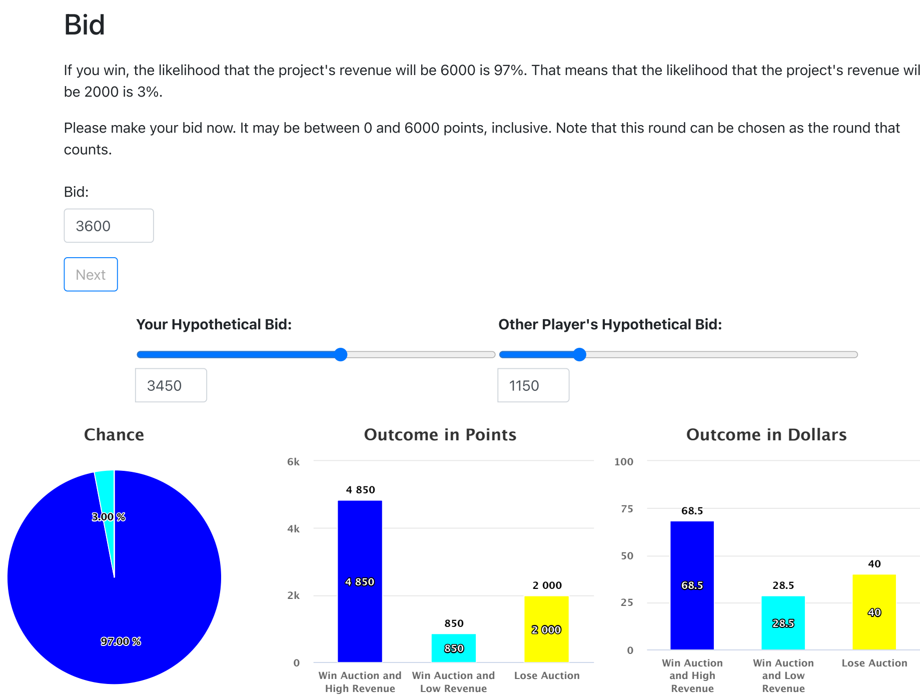


Figure 56: Bidding page for the second-price debt treatment.

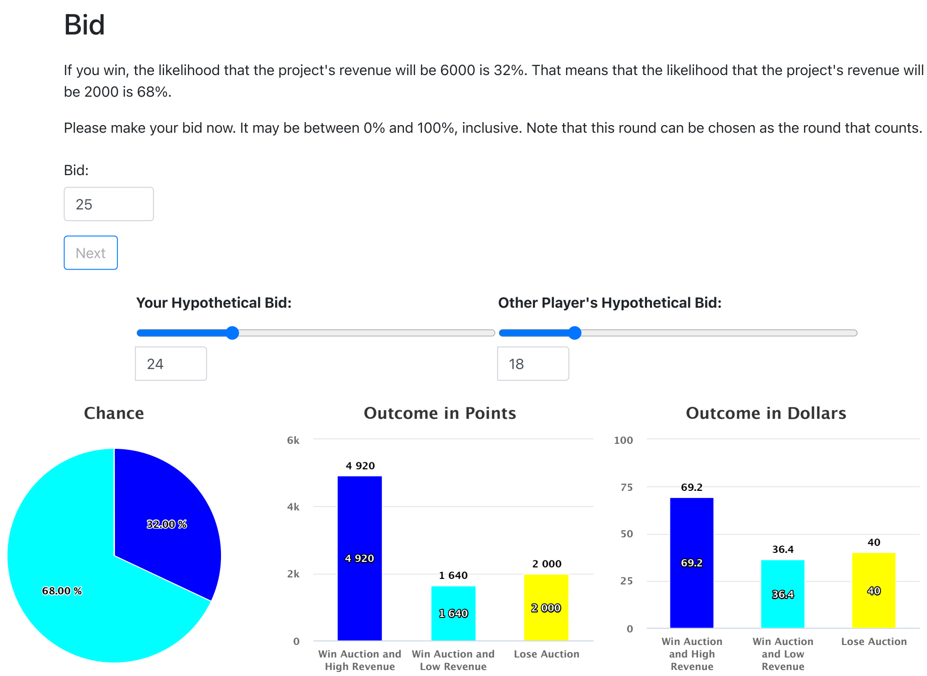


Figure 57: Bidding page for the second-price equity treatment.

Bid

If you win, the likelihood that the project's revenue will be 6000 is 40%. That means that the likelihood that the project's revenue will be 2000 is 60%.

Please make your bid now. It may be in the form of either debt or equity. Debt bids may be between 0 and 6000, inclusive. Equity bids may be between 0 and 100 (%), inclusive. Note that this round can be chosen as the round that counts.

Please choose the security type you will bid with and enter your bid.

Bid type:

Equity

Bid amount:

31

Next

You can use the sliders below to help choose your bid type and amount. Move each slider for the comparison charts to become visible.

Hypothetical equity bid: 20

Hypothetical debt bid: 450

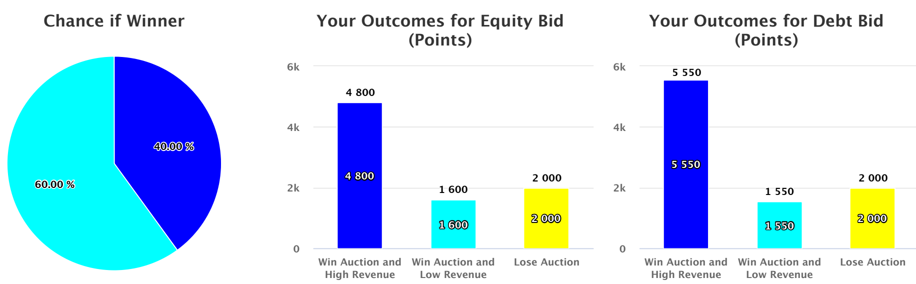


Figure 58: Bidding page for the informal treatment.

Choose

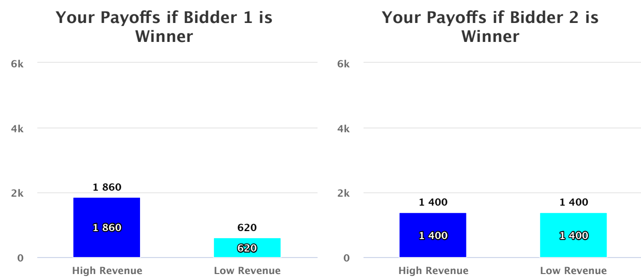
The bidders in this auction have made the following bids. Please review the bids and choose the winner of the auction.

Bidder	Bid Type	Bid
1	Equity	31
2	Debt	1400

The payoffs you will receive if you select Bidder 1 or Bidder 2 as the winner are shown in the diagrams below.

Important: You do not know the chance of receiving the different payoffs.

Important: The chances of receiving the high and low payoff may be different for each bidder.



Please choose which bidder is the winner of the auction. Note that this round may be chosen as the round that counts.

Win choice:

1

Figure 59: Seller choice page for the informal treatment.

Results

You won the auction! Your bid was 2100 points while the second highest bid was 400 points. That means that if this round is chosen for payment, you will have a 61% chance of receiving 3900 points and a 39% chance of receiving 0 points. The other player will receive 2000 points.

Next

Figure 60: Winning result page for the first-price debt treatment.

Results

You won the auction! Your bid was 45% while the second highest bid was 13%. That means that if this round is chosen for payment, you will have a 56% chance of receiving 3300 points and a 44% chance of receiving 1100 points. The other player will receive 2000 points.

Next

Figure 61: Winning result page for the first-price equity treatment.

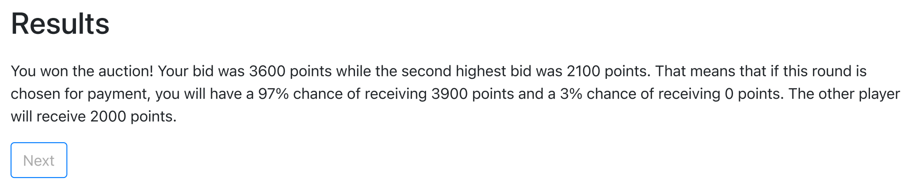


Figure 62: Winning result page for the second-price debt treatment.

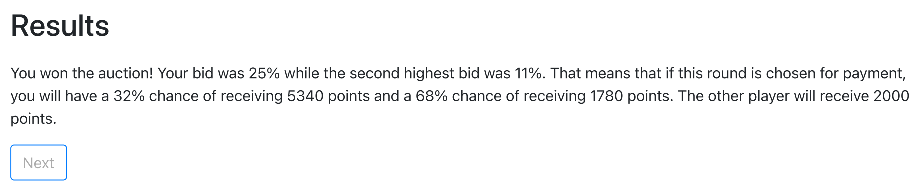


Figure 63: Winning result page for the second-price equity treatment.

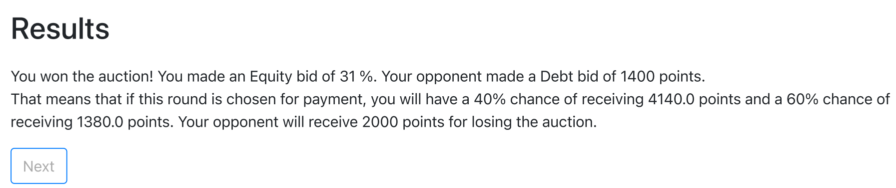


Figure 64: Winning result page for the informal treatment.

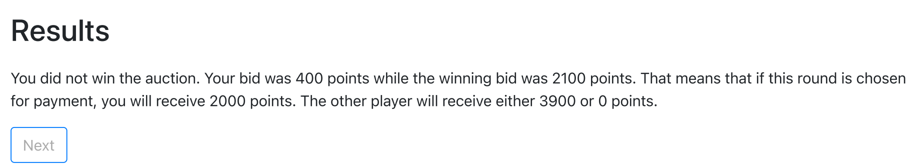


Figure 65: Losing result page for the first-price debt treatment.

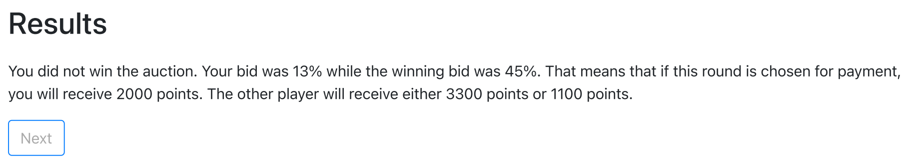


Figure 66: Losing result page for the first-price equity treatment.

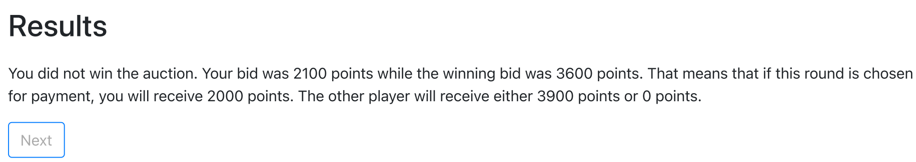


Figure 67: Losing result page for the second-price debt treatment.

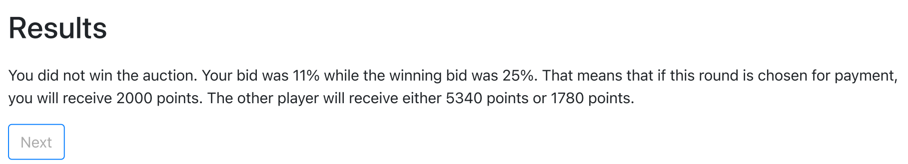


Figure 68: Losing result page for the second-price equity treatment.

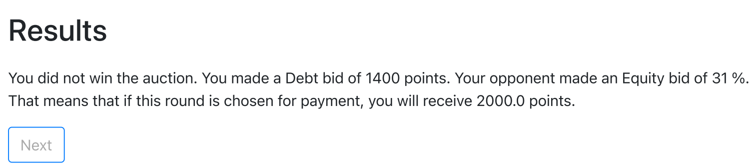


Figure 69: Losing result page for the informal treatment.

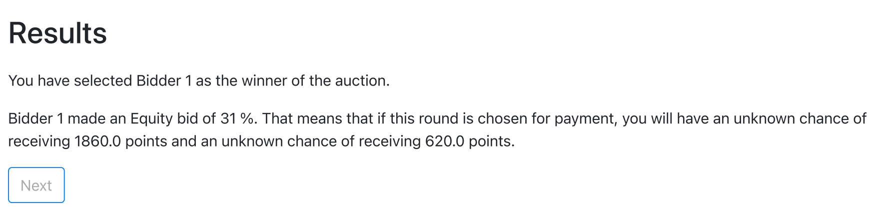


Figure 70: Seller result page for the informal treatment.

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

In this part of the experiment, you will complete 10 rounds of an individual choice task. Every task has an interactive visual aid to assist with picking your preferred choice. In this part of the study, your payoffs will depend only on your choices, and not any other participants' choices.

In every task, you must choose among different options. Your choice will determine a monetary prize and its chance. All of your choices will involve some chance of a monetary prize, otherwise you will get the show-up fee of $20. As you move the slider to the right, the monetary prize will decrease but the chance you will receive the prize will increase. For each task you will have to determine your preferred combination of a positive prize and its chance. The size of the potential outcomes and how their chance changes with the slider will be different for different tasks.

Most choices involve some risk. For example, a choice could be between a 25 in 100 chance of 3000 points, and the corresponding 75 in 100 chance of 0 points. To aid with your choice, there will be a changing display for every possible choice. Therefore, for any choice you will always be able to see the chance of receiving a positive amount.

The next page contains an example to familiarize you with how this works. Take your time and make sure you understand how it works. We will not begin until everybody completes this example.

Very Important: For each task, the slider is a tool to help you decide the choice you like the best. Therefore, it is in your best interest to move it around to help you determine which choice you like better.

Next

Figure 71: Instructions for the Andreoni-Harbaugh task in all treatments.

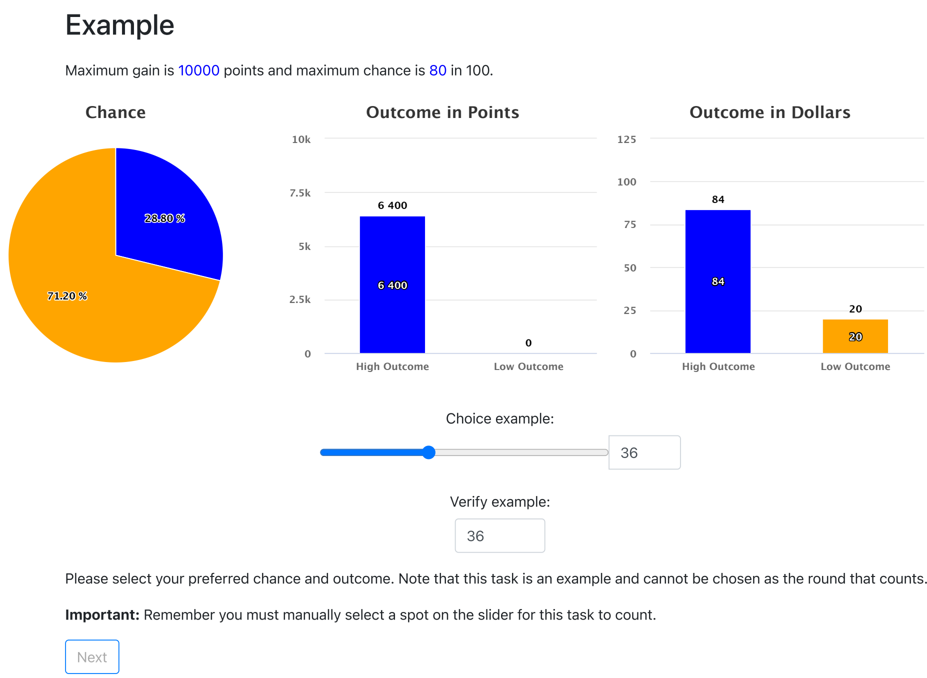


Figure 72: Examples for the Andreoni-Harbaugh task in all treatments.

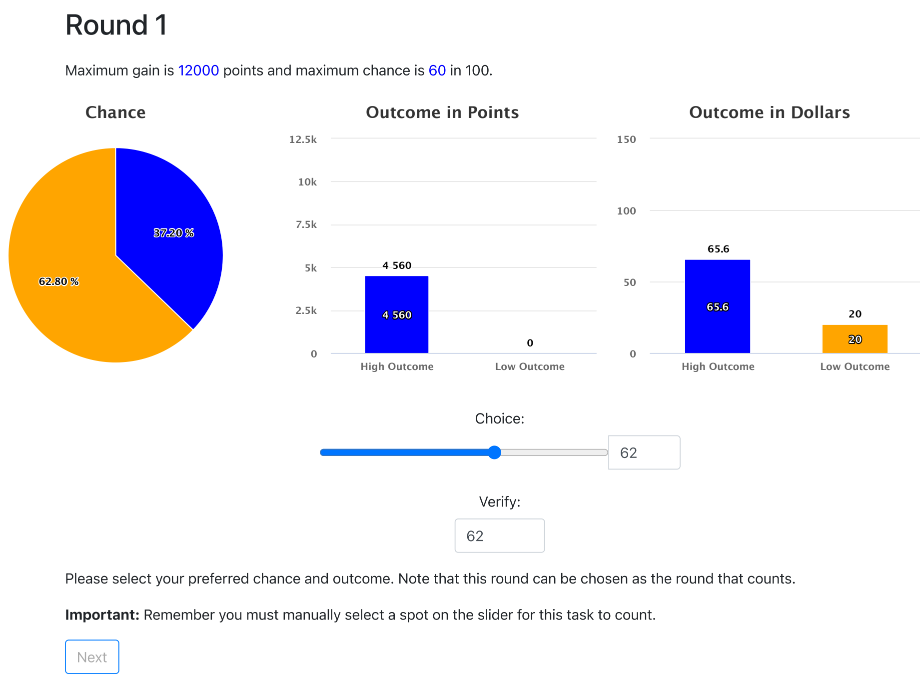


Figure 73: Round 1 of the Andreoni-Harbaugh task in all treatments.