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Preferences and Decision Support in Competitive Bidding

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Abstract

We examine bidding behavior in first-price sealed-bid and Dutch auctions, which are strategically equivalent under standard preferences. We investigate whether the empirical breakdown of this equivalence is due to (non-standard) preferences or due to the different complexity of the two formats (i.e., a different level of mathematical/individual sophistication needed to derive the optimal bidding strategy). We first elicit measures of individual preferences and then manipulate the degree of complexity by offering various levels of decision support. Our results show that the equivalence of the two auction formats only breaks down in the absence of decision support. This indicates that the empirical breakdown is caused by differing complexity between the two formats rather than non-standard preferences.

JEL Classification: D44, D81.
Keywords: Auctions; Decision support system; Experiment; Loss aversion; Preferences.

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1 Introduction

The first-price sealed-bid auction (FSPBA) and the Dutch auction (DA) are two of the most frequently used auction formats. In an FPSBA, bidders simultaneously submit "sealed" bids to the seller and the highest bidder receives the object and pays his bid. In a DA, the seller starts at a high initial ask price and gradually decreases the ask price until the first bidder stops the auction, receives the item, and pays the stop price. With slight variations, both the FPSBA and the DA generate billions of dollars in revenue each year. Governments and private firms frequently use the FPSBA for procurement in construction and to subcontract with suppliers. Federal banks and firms use variants of the DA to sell securities and refinance credit.[1] Furthermore, the DA can be found on fish and fresh-produce markets (e.g., Cassady, 1967).

With regard to the actual implementation of auctions, offline auctions as a mechanism to buy and sell goods is not a new phenomenon, but the specific use of online auctions has experienced tremendous growth in the new media era (Hennig-Thurau et al., 2010).[2] According to Ariely and Simonson (2003), the popularity of online auctions is due to the following three particular features: First, online auctions overcome geographical limitations, such that people from all over the world have the opportunity to submit their bids in any auction. Second, electronic auctions on the Internet allow for more flexibility among sellers and bidders, because the duration of an auction can be several days (or even weeks), and there is the possibility of asynchronous bidding. Third, auctions can be organized at substantially lower costs, which translates into lower commission fees and hence higher participation rates among sellers and buyers.

The increase in the use of Internet-based auctions has led to a rise in the demand for expert services. Indeed, there is an increasing number of consulting firms specializing in auctions (e.g., Market Design Inc.) and major economic consulting companies offer services regarding auctions and bidding (e.g., The Brattle Group, NERA). These services typically include all aspects relevant for setting up and participating in auctions (e.g., bid tracking, bidding strategy, auction rules and design, training, provision of input to regulators). Moreover, the design of decision support systems (DSS) has also attracted considerable interest. For example, several

[1] Note, however, that these examples typically auction off multiple units and that the auctions are then modified such that they usually do not discriminate between different bidders but apply a uniform-pricing rule.

[2] See also Haruvy and Popkowski Leszczyc (2009), who provide an overview of the implications of economically relevant aspects that are characteristic of Internet auctions.

patents have been filed for (automated) bid-advising systems that account for, e.g., the auction structure and risk attitudes of rival bidders based on historical data.[3] At the same time, technological advances and the use of Internet auctions means that relevant information can be provided more easily and faster in the course of an online auction. We take these observations as a starting point to address the implications of decision support systems in different formats of (online) auctions.[4]

Theory suggests that the FPSBA and the DA yield the same revenue as both formats are strategically equivalent. However, this strong theoretical result breaks down empirically. Previous research suggests three possible explanations: opportunity costs (Carare and Rothkopf, 2005; Katok and Kwasnica, 2007), preferences (Weber, 1982; Nakajima, 2011; Lange and Ratan, 2010; Belica and Ehrhart, 2013; Ehrhart and Ott, 2014), and complexity of the decision (Cox et al., 1983). We analyze the role of preferences and complexity while controlling for opportunity costs. Our results indicate that the non-equivalence is driven by the difference in complexity of competitive bidding in the two auction formats rather than by individual (non-standard) preferences.

The empirical breakdown of this equivalence is a robust observation in experimental settings both in the laboratory and in the field. However, the direction of the deviation is non-conclusive. On the one hand, Coppinger et al. (1980) and Cox et al. (1982) find that the FPSBA yields higher revenue than the DA in a controlled laboratory setting. On the other hand, in a field experiment on an Internet auction platform, Lucking-Reiley (1999) finds that the DA generates higher revenue than the FPSBA.

Differences in opportunity costs can explain these differences. In a DA, bidders have an incentive to accept a high price and stop the auction early, because they have to frequently monitor the price clock or even have to physically return to the auction site to check for updates in prices as long as the auction is running. Such costs do not occur in the (static) FPSBA which ends immediately after the (simultaneous) submission of bids.

Carare and Rothkopf (2005) show theoretically that such increased opportunity costs increase the optimal bid. In a DA, Cox et al. (1983) and Katok and Kwasnica (2007) analyze the trade-off between opportunity costs and additional utility from suspense, i.e., from a joy of

[3]See, for example, Guler et al. (2002, 2003, 2009); Zhang and Guler (2013).

[4]Adomavicius et al. (2013) and Bichler et al. (2017) who analyze the role of decision support systems in combinatorial auctions.

gambling. Both articles provide evidence that increasing opportunity costs by increasing payoffs or by decreasing the clock speed, respectively, increases bids in a DA. In contrast to their approach, our goal is to assess the predictive power of different preference-based theories for observed bidding and to analyze the effect of complexity. Hence, we eliminate confounding differences in opportunity costs by holding the time per auction format and thus the opportunity costs from participation constant. In addition, we hold the action set, i.e., the set of feasible bids, constant across the two formats which allows a direct comparison of the two auctions.

In the absence of opportunity costs, the strategic-equivalence result rests on the assumption that bidders have standard preferences, i.e., they derive utility only from realized personal payoffs. In addition, the utility function is global in the sense that the effect of wealth changes does not depend on whether such changes occur in the gain or loss domain or whether they are certain or generated by a lottery. With regard to the departures from standard preferences, we study expectations-based reference-dependent and Allais-type preferences. We focus on these two specifications, because they are frequently used to explain decision making under uncertainty.[5]

Under reference dependence, the bidder compares gains and losses in wealth relative to a reference point (Kahneman and Tversky, 1979). In this comparison, the bidder is assumed to be loss averse and puts more weight on negative deviations from this reference point (losses) than on equivalent positive deviations (gains). Loss aversion contradicts the global-utility assumption of standard preferences because the bidder considers changes in wealth with respect to a local reference point. The specification of the reference point is subject to debate. Kőszegi and Rabin (2006, KR) propose expectations-based reference dependence, i.e., the reference point is stochastic and given by the rational expectations that the individual holds over the outcomes of a risky decision. In the following, we will denote expectations-based reference-dependent preferences as *KR preferences*.

Individuals with *Allais-type (AT) preferences* prefer outcomes that are generated with certainty to the same outcomes that are generated by a risky lottery (e.g., Andreoni and Sprenger, 2010). This difference is most prevalent in the Allais paradox (Allais, 1953). Here, subjects prefer a degenerate lottery over a risky one with a higher expected value but reverse their choice

[5]Reference dependence as proposed by Kahneman and Tversky (1979) is the most cited theory on risky decision making (Kim et al., 2006). Allais-type preferences are an early critique of expected utility theory (EUT) (Allais, 1953) and are empirically very robust in explaining deviations from predictions under standard preferences (Kahneman and Tversky, 1979; Camerer, 1989; Weber, 2007).

if both lotteries are monotonically transformed and become both risky (the so-called common-ratio effect, CRE). This reversal is inconsistent with standard preferences as it violates the crucial independence axiom of EUT (Savage, 1954; Anscombe and Aumann, 1963). According to this axiom, decisions between lotteries should not depend on consequences that do not differ between the lotteries.

We make use of data from a two-stage experiment in which we first elicit the preferences of all subjects that participate in our experiment. In this first stage, we utilize the procedure of Abdellaoui et al. (2007) and elicit individual preferences in a fully non-parametric procedure, i.e., without imposing any assumption on the functional form of utility. Furthermore we measure to what extent participants exhibit Allais-type preferences by utilizing a metric version of the CRE (e.g., Beattie and Loomes, 1997; Dean and Ortoleva, 2014; Schmidt and Seidl, 2014).

Preference theories assume Bayesian rationality in the sense that bidders derive and process probabilities correctly. However, bidding in auctions can be a demanding problem. In deriving the optimal bid, the bidder faces a trade-off between increasing his winning probability by submitting a higher bid and increasing his winning profit by submitting a lower bid. Individual preferences determine the optimal bid that balances these diametric effects. However, this optimization requires a certain level of mathematical sophistication. It is thus possible that the observed differences between bidding behavior is due to different levels of complexity of the two auction formats. In other words, bidders can make mistakes, e.g., in deriving the winning probability associated with their bid, and these mistakes might differ between the two formats.

We design a DSS to reduce the complexity and assist bidders in deriving the optimal bid that corresponds to their individual preferences. We vary the auction format within-subjects and the level of decision support between-subjects. Subjects either have no decision support (No DSS treatment) or they have medium (Medium DSS treatment) or full support (Full DSS treatment) to assist bidding. The decision support system is a computerized overlay displaying additional information. Medium DSS shows the winning probability whereas Full DSS additionally provides expected profits. Although this information is redundant for fully rational decision makers, it is non-trivial to derive and providing such information greatly reduces the complexity of optimal bidding.[6]

[6] Our implementation of decision support is primarily a mean to analyze the role of complexity in competitive bidding, the design of such DSS is also of interest in itself. Several patents have been filed for (automated) bid-advising systems that account for, e.g., the auction structure and risk attitudes of rival bidders based on historical data (see, e.g., Guler et al., 2002, 2003, 2009; Zhang and Guler, 2013).

Our results highlight the role of decision support systems. In line with the literature, we find significant differences between auction formats when bidders do not receive decision support. However, differences vanish between participants once we provide decision support. This indicates that the observed differences in bidding behavior between the FPSBA and the DA are due to different levels of complexity rather than non-standard preferences. In addition, our tests show that bidding behavior strongly depends on participants' risk aversion. The influence of individual loss aversion and Allais-type preferences is not significant and cannot explain differences in bidding behavior. Our results thus highlight that from a consulting perspective, it seems to be more important to support decision makers in the derivation of optimal bidding strategies than to focus on the choice of the auction format.

The paper proceeds as follows. The next section introduces the model environment and theoretically analyzes the effect of different preference specifications on optimal bidding in the FPSBA and the DA. Section 3 presents our experimental design and our implementation of decision support. We report our results in Section 4. Section 5 concludes.

2 Theory

In this section, we first describe the two auction mechanisms. We then characterize the equilibria in both auction formats for standard preferences (SP), Köszegi-Rabin (KR) preferences, and Allais-type (AT) preferences. We analyze the optimal bidding behavior of one bidder given a bidding strategy of the competitor.

In both auction formats, two bidders compete for one indivisible item and the highest bidder wins. Let $P = \{p_1, \ldots, p_n\}$ be a discrete price grid. In the FPSBA, each bidder places a *bid* $b \in P$ at which he is willing to buy the item. In the DA, each bidder decides for every *ask* $a \in P$ whether to accept it or not. In the FPSBA, the *price* corresponds to the highest bid, whereas in the DA, it corresponds to the highest accepted ask. The winning bidder receives the item and pays the price. If the bidder does not win the auction, he does not receive the item and does not pay anything.[7] In both auction formats bidders face a trade-off between improving their probability of winning and increasing their profit in case of winning.

Our DSS implementation resembles such automated bidding advice that estimates competitors' bidding behavior in a given auction format.

[7]Ties are broken at random with equal probability to receive the item.

To derive the equilibrium bidding strategy in the discrete FPSBA, we follow Cai et al. (2010). For the dynamic course of the DA, we adopt the modeling approach of Bose and Daripa (2009). In the DA, the seller starts the auction with the highest ask p_n. She then approaches each bidder sequentially asking whether or not the bidder accepts that ask. Which bidder is asked first is randomly determined at the beginning of each offer. Each bidder has the same chance to be asked first. In case that the bidder who is asked first rejects the offer, the seller offers the same ask to the other bidder.

2.1 Standard preferences

The term standard preferences covers all preferences that are purely outcome-based and only consider the own payoff. This means an individual has standard preferences if the utility function is global and only depends on one's own payoff (DellaVigna, 2009).

Proposition 1 (Standard Preferences)**.** *The FPSBA and the DA are strategically equivalent, which implies that they yield the same revenue (Vickrey, 1961).*

The crucial observation to this result is that the information revealed during the descending of the price clock in the DA does not change the trade-off between a bidder's winning probability and his profit in case of winning. Suppose a bidder bids $b = p_k$ in an FPSBA. This bidder enters a DA with the plan to accept the ask $a = p_k$, because the ex-ante problem is identical for the two formats. As the price clock is approaching p_k, two things may happen. First, the competitor accepts an ask greater than p_k. In this case, the auction ends and the bidder cannot react to this information. Second, the price continues to fall which increases the probability to win. However, the marginal trade-off stays the same. This is due to the fact that a bidder derives his optimal bidding strategy under the assumption that he has the highest valuation. Hence, the bidder sticks to his plan and waits for the ask p_k.

2.2 Expectations-based reference points

In contrast to individuals with standard preferences, an individual with reference-dependent preferences does not only care about his absolute payoff, but also compares the outcome to a reference point. Therefore, the utility function of such a bidder consists of two parts. First, the term $u(x)$ corresponds to utility derived from payoff x as under standard preferences. Second, the term $n(x,r)$ corresponds to gain-loss utility that evaluates the outcome x against a reference level r (Kahneman and Tversky, 1979). Following the approach of Kőszegi and Rabin (2006) the gain-loss utility is defined piece-wise as

$$n(x,r) = \mu\left(u(x) - u(r)\right),$$

where

$$\mu(z) := \begin{cases} \eta z & \text{if } z > 0 \\ \eta\lambda z & \text{if } z \leq 0. \end{cases}$$

Here $\eta > 0$ determines how important the relative component is compared to the absolute payoff. Furthermore, λ represents the level of loss aversion which weighs negative deviation from the reference point (losses) relative to positive deviations (gains). If $\lambda > 1$, the bidder is loss averse, i.e., losses hurt him more than equally sized gains please him. If $\lambda = 1$, the agent is loss-neutral, and if $\lambda < 1$, the agent is gain-seeking. Total utility is the sum of both parts and given by $u^{\text{KR}}(x,r) = u(x) + n(x,r)$. We follow the literature and focus on the effect of loss aversion by assuming that utility of payoff $u(x)$ is linear. Hence, gain-loss utility $n(x,r)$ is a two-piece linear function.

Kőszegi and Rabin (2006) assume that the reference point is stochastic and formed by the rational expectations of the bidder. They introduce the concept of a *personal equilibrium* which requires that the bidder has rational expectations about his own behavior and behaves consistently with his plans. Specifically, they propose that the bidder evaluates each possible outcome x under the winning probability $\Pr(x|b)$ against all other possible outcomes under this distribution. This modification has recently been successful in describing various empirical observations from laboratory endowment effects to labor supply in the field (e.g., Sprenger, 2010; Ericson and Fuster, 2011; Crawford and Meng, 2011).

Proposition 2 (Expectations-based reference point)**.** *A revenue ranking of the FPSBA and the Dutch auction is not possible.*

In the FPSBA, loss aversion implies that bidders want to reduce the difference between the payoff in case of winning and in case of losing the auction. As a consequence, subjects with a higher degree of loss aversion place higher bids than less loss-averse subjects. In the FPSBA, there exists an almost everywhere unique optimal bidding strategy (Eisenhuth and

Ewers, 2012).

In contrast to the FPSBA, there might be several consistent bidding strategies in the DA. For example, it may be optimal for a subject to accept a high offer p if it planned to do so, whereas it is optimal for the same subject to wait for a smaller offer p' if her initial plan was to accept only a small offer p'. Different plans induce different reference points and thereby different optimal bidding strategies. Since several reasonable reference points can exist in the DA, we do not get a unique bidding prediction but a set of optimal bidding strategies. Applying a refinement and identifying the bidding strategy with the highest expected utility might not be possible as the optimality of a bidding strategy can change during the dynamic course of the auction (Ehrhart and Ott, 2014).

As shown in the Appendix A.2.3, it may well be the case that for a given valuation the lowest optimal bid in the DA is lower than the optimal bid in the FPA, whereas the highest optimal bid in the DA is higher than the optimal bid in the FPA. As a consequence, a revenue ranking is not possible in general.

2.3 Allais-type preferences

Allais-type preferences violate the independence (or substitution) axiom, which is essential for EUT (Allais, 1953; Savage, 1954; Anscombe and Aumann, 1963). The independence axiom states that an individual who is indifferent between two lotteries should also be indifferent between these lotteries if the probabilities of both lotteries are multiplied by $\rho \in (0, 1]$. That is, if one scales the probabilities of both lotteries by a common ratio, the preference ordering is not affected under EUT. Grimm and Schmidt (2000) show that this independence requirement is a necessary and sufficient condition for strategic equivalence between the FPSBA and the DA.

Kahneman and Tversky (1979) report that subjects have a preference for certainty, i.e., outcomes in a degenerate lottery. In their experiment, a majority of individuals reveals that they prefer a degenerate lottery over a risky one but reverse this choice if both lotteries are scaled by ρ such that both now become risky. Thus, participants violate the independence requirement. This so-called "Allais paradox" (Allais, 1953) is empirically very robust, although reverse Allais-type preferences (i.e., a preference for risky outcomes if a certain outcome is available) have also been observed experimentally (Camerer, 1989; Weber, 2007).

Proposition 3 (Allais-type preferences)**.** *The DA yields higher revenue than the FPSBA if* *bidders have Allais-type preferences. The FPSBA generates higher revenue if bidders have reverse Allais-type preferences (Weber, 1982; Nakajima, 2011).*

The intuition is that the current price in the DA is augmented by a psychological premium for certainty for individuals with Allais-type preferences. This premium makes it more attractive to accept a high price in the DA than in the FPSBA in which all bids imply uncertainty. In other words, the DA offers a certain payoff in the given round against a risky lottery (prices in future rounds), whereas the FPSBA only offers a risky lottery.[8]

3 Experiment

In this section, we first introduce our experimental design and then review previous research that examines the equivalence of the first-price sealed-bid auction and the Dutch auction experimentally.

3.1 Design

Each subject participated in 18 FPSBA and 18 DA. Each auction consists of one participant and one bidding robot as bidders. The valuations of the participant are drawn from the set $\{6, 10, 14, 18, 22, 26, 30, 34, 38\}$ EUR. In each format, every participant is assigned each valuation twice in order to make participants' bidding behavior as comparable as possible. The bidding robot draws one price from $P = \{0, 1, \ldots, 21\}$ EUR according to a uniform distribution. This realization is the robot's bid in the FPSBA and its stopping price in the DA. We use a bidding robot as the competitor for three reasons. First, we do not want our results to be confounded by other-regarding preferences that are not considered in any of the models presented in Section 2. Second, we effectively reduce the strategic problem to a decision problem by fixing the strategy of the competitor. This makes it easier for subjects to focus on their optimal strategy by breaking the dynamics of higher-order beliefs.[9] Third, we are able to precisely calculate the

[8] We note that this overbidding only works given our organization of the DA, because we resolve the order in which the seller approaches the two bidders at the beginning of each period. If we had broken ties at random after each round, which is frequently done in DA implementations, the current price would actually be risky as well and Allais-type preferences would coincide with standard preferences.

[9] Note that most work that analyzes strategic interaction in auctions assumes that subjects' preferences are common knowledge and that only valuations are private information. However, one cannot ensure common knowledge in reality.

winning probability and the expected profit. The provision of this information depends on the DSS treatment status.

Auction formats

In our experiment, we analyze the following two auction formats:

- **FPSBA** In the FPSBA, the computer screen informs the participants about their valuation and features a testing area. In this area, participants can explore the consequences of a particular bid on their profit and, depending on the DSS treatment, on the winning probability and the expected profit (see below). Participants are further informed about the remaining time of the current round. Finally, they enter their actual bid and submit this bid by pressing a button. After submitting their bid, participants are immediately informed whether they have won the auction and about the remaining time the current auction lasts. When the round has timed out, a feedback screen informs the subjects about their valuations, the winning bid, whether or not they received the item, and their profit for the this round.

- **DA** In the DA, the computer screen informs participants about their valuation and displays the current price, the time until the next price, and the next price. As in the FPSBA, participants are informed about their profit given both the current and the next price. Depending on the DSS treatment, participants are also informed about the probability to be offered the current price and the next price as well as the associated expected profits (see below). Finally, participants can accept the current price by pressing a button. After either the participant or the computer bidder has accepted the current price, participants are immediately informed whether they have won the auction and about the remaining time the current auction lasts. When the round has timed out, participants receive the same feedback as in the FPSBA.

Decision support system

The theoretical analysis on the role of preferences in Section 2 highlights the fact that deriving the optimal bid depends on the following aspects: (i) the profit from winning with the chosen bid, $v^i - b^i$, (ii) the probability to win with the chosen bid, $\Pr\left(\text{win}|b^i\right)$, and (iii) the expected utility derived from the combination of the former two. The latter depends on the individual preferences whereas the former two are identical across all theories. Hence, we design a DSS that assists the bidder by providing (i) the profit from winning, (ii) the winning probability, and (iii) the expected profit which is the product of (i) and (ii).

Any deviation from bidding predictions can result from two sources: an omitted preference specification or problems in deriving the optimal bid. Our DSS allows us to disentangle the role of preferences from the impact of a lack of mathematical sophistication (complexity). This is because in the experiment, we fix the bidding strategy of the competitor and hence reduce the strategic problem of finding mutual best responses to the problem of finding a one-sided best response (i.e., an optimization or decision problem). We can thus objectively state expected profits and winning probabilities that should help participants derive the bid that maximizes the expected utility based on their actual preference specification. In other words, we implement the DSS to analyze whether observed bids are due to the underlying preferences or the complexity of the auction.

Specifically, the DSS varies between participants regarding the information a bidder receives during an auction. There are three nested levels of DSS: No, Medium, and Full DSS. In the FPSBA, the information is given for the current test bid. In the DA, the information is given for both the current and the next price. We vary the information content of the DSS between participants. The information content in each condition is as follows:

- **No DSS** In the FPSBA, subjects see the *profit if bid is successful* which is the profit their test bid would generate given that they won the auction. In the DA, subjects see the *profit at given price* which is the profit they would make if they accept the current price or if they now decide to accept the next price.

- **Medium DSS** Subjects have the same information as in No DSS. In addition, in the FPSBA, they also see the *winning probability* of their test bid which is the probability of having a higher bid than the competitor plus the probability of having the same bid and being selected as winner by the tie-breaking rule. In the DA, subjects receive the *probability to be offered the given price* for both the current and the next price. The probability to receive the current price p_k is trivially given by 1. However, the probability to be offered the next ask, H^i_k, is highly non-trivial to derive (see Section A.2.2 for details).

- **Full DSS** Subjects have the same information as in Medium DSS. In addition, in the FPSBA, they also see the expected profit of their test bid. In the DA, subjects see the expected profit of the next price. In the FPSBA, the expected profit is the product of the winning probability and the profit if the bid is successful. In the DA, the expected profit is the product of the probability to be offered the given price and the profit at the given price.

We are not aware of any other work that incorporates decision support in auctions. Armantier and Treich (2009) elicit both subjective probabilities and risk preferences in an attempt to find an explanation for overbidding in experimental first-price auctions. The authors report that participants underestimate their winning probability and overbid. Furthermore, they investigate the effect of a feedback system regarding winning probabilities. The feedback is implemented as follows. Participants are asked to predict their winning probability and they are given feedback regarding the precision of their prediction at the end of each round. As such, their feedback system is designed to induce learning whereas learning is not necessary in our setup as participants are given support before (FPSBA) or during (DA) the auction. They show that overbidding is reduced if their feedback system is in place.

Subjects

Table 1 provides an overview of participants characteristics in the different treatments.

Risk aversion is measured as the are under the curve on the gain domain, i.e. the integral of the estimated utility function on the gain domain. We normalize the domain of utility to [0,1] by dividing each elicited gain by the maximum gain. We interpolate linearly between the elicited points and use a geometric approach to calculate the area. In case of risk aversion the measure is smaller 0.5. A risk seeking individual has a measure larger than 0.5 and a risk neutral subject has a measure equal to 0.5.

Loss aversion relates the slope of utility in the gain domain to its slope in the loss domain. Kahneman and Tversky (1979) define loss aversion by $-u(-x) > u(x)$ for every $x > 0$. We measure the coefficient of loss aversion as the mean of $-u(-x)/u(x)$ for all elicited values x.

Allais-type preferences are measured by metric measure of the common-ratio effect (CRE) to assess the preference reversal due to violations of the independence axiom. Participants exhibiting the common-ratio effect show a preference reversal such that, they have a preference for certain outcomes. Participants with a CRE of 0 are consistent with expected utility theory, a CRE larger zero indicates Allais-type preferences and subjects with a CRE smaller zero have reverse Allais-type preferences.

Subjects' numeracy is rated according to a combination of the Schwartz et al. (1997) and the *Berlin Numercy Test* that assess the understanding of fundamental concepts of probability. Subjects have to answer seven questions and the variable numeracy reflects how many of these questions were answered correctly.

Table 1: Summary statistics by treatment

Treatment	No DSS		Medium DSS		Full DSS		
First format	FPSBA	DA	FPSBA	DA	FPSBA	DA	p-value
Risk aversion	0.461	0.466	0.499	0.528	0.441	0.526	0.52
	(0.167)	(0.105)	(0.106)	(0.140)	(0.143)	(0.103)	
Loss aversion	1.842	1.396	1.673	1.352	2.088	1.407	0.08
	(0.860)	(0.474)	(0.713)	(0.506)	(0.842)	(0.450)	
Allais-type	2	2.714	3.857	3.667	4.333	2.267	0.90
	(13.90)	(2.301)	(4.605)	(6.199)	(9.566)	(18.25)	
Numeracy	4.333	4.714	3.929	4.833	4.167	4.867	0.24
	(1.291)	(2.199)	(1.141)	(1.267)	(1.403)	(0.990)	
Participants	15	14	14	12	12	15	

Notes: Reported are means of each variable with standard deviation in parentheses. The last column presents the results of a Kruskal-Wallis tests for the equality of populations.

Organization

The auctions were the second stage of the experiment. In the first stage, which was conducted one week before the second, participants' preferences were elicited. Detailed results are reported in Zeppenfeld (2015).[10] Both stages of the experiment were conducted in the Cologne Laboratory for Economic Research (CLER) at the University of Cologne, Germany.[11] Using the recruiting system *ORSEE* (Greiner, 2015), we invited a random sample of the CLER's subject pool via email. The whole experiment was computerized using the programming environment *z-tree* (Fischbacher, 2007).

In both stages, payoffs were stated in Euros (EUR). Participants were paid out in private for the entire course of experimentation after the completion of the second stage. In the second

[10] The first stage of the experiment was the same for all participants and participants only learned their earnings of the first part until the very end of the entire experiment, i.e., after they completed the second stage.

[11] See www.lab.uni-koeln.de.

stage, one auction of each auction format was randomly chosen to be payoff-relevant. All 82 participants were paid their total net earnings, i.e., their earnings from the auctions and their earnings from first stage of the experiment. The average payoff for the entire experiment was 36.63 EUR corresponding to approx. 45.54 USD at the time of the payment.[12]

3.2 Opportunity costs and action sets

Previous research argues that differences between the two mechanisms come from the heterogeneous organization of the two auctions. The FPSBA is faster, as it only requires to place simultaneous bids and the winner can be announced immediately after all bids are collected. The DA, on the other hand, requires a certain time interval for the clock to reach the desired price level of an individual bidder. Hence, a bidder in a DA faces substantial waiting costs. Carare and Rothkopf (2005) analyze the effect of transaction costs that accrue from the necessity to return to the auction site to check whether the desired price level has been reached. Not surprisingly, facing these additional costs, a bidder is willing to stop the auction at a higher price to avoid the need to return to the auction site.

Cox et al. (1983) and Katok and Kwasnica (2007) analyze the following trade-off experimentally. Despite the fact that bidders face transaction and/or opportunity costs from slow DA's, they also enjoy the "waiting game", as it implies a certain level of suspense. Cox et al. (1983) do not find that tripling payoffs, and therewith increasing the opportunity costs of playing the waiting game, significantly increases bids in a DA. Hence, they reject the hypothesis of "suspense utility". Katok and Kwasnica (2007) find that increasing the clock time, i.e., the time between consecutive price ticks, significantly increases bids in a DA. Slow clocks increase opportunity costs which have to be paid no matter if the bidder wins the auction or not. Katok and Kwasnica (2007) note that in the laboratory, these opportunity costs correspond most likely to participants' value of leaving the laboratory earlier. Hence, a bidder is willing to accept a higher ask to reduce the time to complete the experiment and save opportunity costs.

We account for opportunity costs in two ways. First, we hold opportunity costs constant across treatments. We follow Turocy et al. (2007) and keep the time per mechanism constant. This means that we fix the absolute time per mechanism irrespective of how fast participants

[12]The first stage elicited preference parameters across gains and losses. Total net payoffs across the entire experiment range from −3.00 EUR (−3.73 USD) to 98.45 EUR (122.41 USD). The one subject who accumulated negative payoffs paid in cash at the end of experiment.

decide (FPSBA) or how early they stop (DA). One round of bidding in the FPSBA always lasts 60 seconds.[13] One round of bidding in the DA always lasts 220 seconds, i.e., ten seconds per price tick (see below for a motivation). If a participant accepts a current ask, he wins the auction, but the next round does not start before the 220 seconds are over.[14] Second, all subjects play both the FPSBA and the DA.

Katok and Kwasnica (2007) show that the clock speed has great impact on the bids in a DA due to the implied differences in opportunity costs. Because we hold opportunity costs constant, this is not an argument in our experiment. Participants in the FPSBA have 60 seconds to arrive at a bid that balances the trade-off between the winning probability and the profit in case of winning. We determine the clock speed in the DA based on two considerations. On the one hand, the trade-off between two consecutive price ticks in a DA is easier to compute and participants should need less time. On the other hand, we have to provide some time for the reference point to form. We therefore decide on a clock speed of ten seconds. This is the same clock speed as in the middle treatment in Katok and Kwasnica (2007). However, in contrast to their experiment subjects cannot reduce the duration of the DA in our experiment, as each DA lasts for 220 seconds.

In addition to controlling opportunity costs, we also hold action sets constant across the two mechanisms. In Cox et al. (1983), participants' bids are rounded to the next feasible bid in the DA. Participants can then either confirm or alter this rounded bid. In Katok and Kwasnica (2007), participants can bid integers in the FPSBA, whereas price decrements in the DA were five tokens. In contrast, in our design, participants in the FPSBA face the same set of possible prices as in the DA. This is a direct transfer of our model environment to the laboratory and ensures strict comparability between the two mechanisms.

4 Results

In this section, we report the results of the second stage of our laboratory experiment and focus on the comparison of the FPSBA and the DA. We only consider winning bids, because we only observe a participant's bid in the DA if a participant stopped the auction and won. In

[13] If participants do not enter a valid bid by the end of this time limit, they do not participate in the auction in that round.

[14] In both mechanisms, after the auction has ended, participants see a screen showing the remaining time until the round is completed and whether or not they have won the auction.

order to derive a one-dimensional measure of individual bidding behavior, we first conduct OLS regressions without constants for each participant. Regressing without a constant corresponds to the assumption that a bidder with a valuation of zero behaves rational and places a bid of zero. This gives us the average slope of a subjects bidding function. The steeper the slope the more aggressive is the subject's bidding behavior. Each participant represents one independent observation, because there was no interaction between participants. We report results of non-parametric Wilcoxon signed rank (SR), Mann-Whitney-Wilcoxon (MWW), or Kruskal-Wallis (KW) tests.

In line with the observations by Coppinger et al. (1980) and Cox et al. (1982), we find that individuals place higher bids in the FPSBA than in the DA (MWW: $p = 0.0183$). However, a closer look reveals that bidders only place higher bids in the FPSBA than in the DA if they get no decision support (MWW: $p = 0.0046$). The No DSS treatment is comparable to standard experimental auction designs. If bidders get (some) decision support, the differences vanish (MWW: Medium DSS $p = 0.1498$ and Full DSS $p = 0.6256$). Table A.2 complements these tests controlling for bidder characteristics. It confirms the observation that bids in the DA are substantially lower than in the FPSBA in absence of decision support ($p < 0.001$) and that this differences vanish once support is provided (Medium DSS $p = 0.1628$, Full DSS $p = 0.8044$).

In the FPSBA, the provision of decision support changes the bidding behavior significantly (KW: $p = 0.0704$). Bidders who receive decision support (Medium DSS, Full DSS) place lower bids than bidders without decision support (No DSS; MWW: $p = 0.0214$). In contrast, the influence of decision support is overall not significant in the DA (KW: $p = 0.1224$). However, we find some evidence that the effect of decision support works in the opposite direction compared to the FPSBA, i.e., bidders who only receive limited decision support (No DSS, Medium DSS) place smaller bids than those bidders who get full decision support (Full DSS; MWW: $p = 0.0424$).

Figure 1 illustrates the bidding behavior and Table 2 presents the results of Tobit panel regressions analyzing the influence of elicited preferences and of decision support in the FPSBA and the DA. Controlling for individual characteristics, the regressions support the results of our non-parametric tests. The provision of decision support (Medium DSS, Full DSS) decreases bids in the FPSBA. In contrast to that, in the DA the provision of Medium DSS does not influence bidding behavior ($p = 0.679$) and the influence of Full DSS is also not significant ($p = 0.106$).

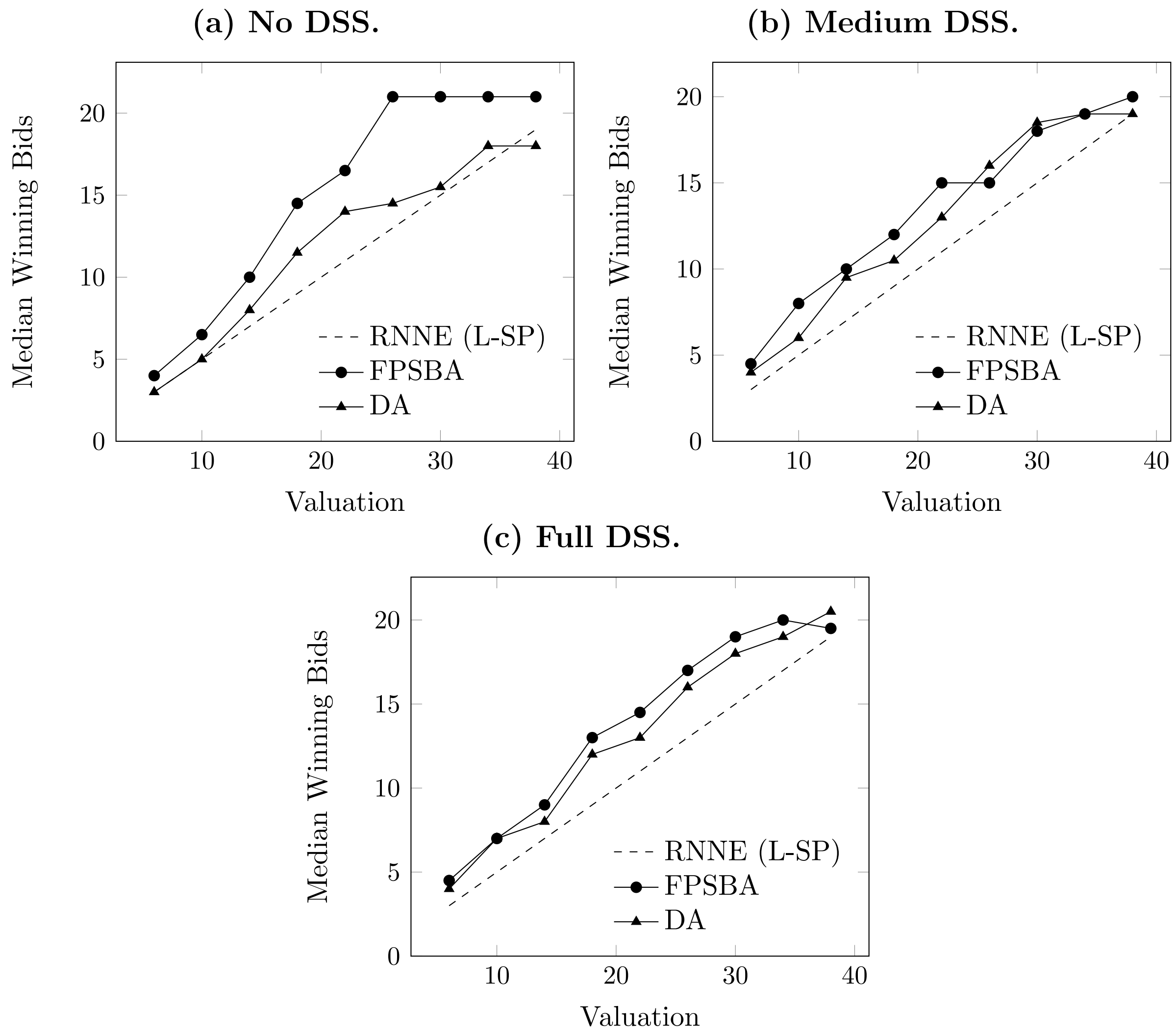
The regressions further show that risk-averse bidders place higher bids, which is in line with other experimental studies (See for example Bichler et al., 2015). Our measures of individual loss aversion and Allais-type preferences have no or only marginal influence on bidding behavior. Theories based on Allais-type preferences predict higher bids in the DA than in the FPSBA, something we do not observe. In the DA we find some indication that subjects with a higher numeracy score place lower bids. However, the significance vanishes if we do not control for risk aversion.

Table A.1 complements Table 2 and examines if the elicited preferences (risk aversion, loss aversion, Allais-tpye preferences) and characteristics (numeracy) have different effects on bidding behavior in the two auction formats. We only find weak evidence that a higher numeracy score leads ceteris paribus to lower bids in the DA than in the FPSBA, but no indication that any of the elicited preferences can explain differences in bidding behavior. Cox et al. (1983) argue that differences between the two mechanisms result from violations of Bayes' rule and indirectly test this conjecture by tripling individual payoffs which increases opportunity costs from miscalculations. In contrast, our design is a direct test of the impact of cognitive limitations and we find additional evidence for this conjecture.

Similar to the other experimental papers that compare bidding behavior in the FPSBA to bidding behavior in the DA (Cox et al., 1983; Katok and Kwasnica, 2007), participants in our experiment first played 18 rounds in the DA and then another 18 rounds in the FPSBA.[15] In contrast to the findings of Cox et al. (1983); Katok and Kwasnica (2007), we find that neither subjects who first participate in the FPSBA nor subjects who start in the DA change their bidding behavior when the auction format changes (SR: FPSBA $\rightarrow$ DA, $p = 0.3888$; DA $\rightarrow$ FPSBA, $p = 0.1973$). This within-participant consistency is in contrast to the literature and we relate this finding to the strict comparability of the two formats in our experiment. Hence, our bidding data indicates that a constant action set and fixed opportunity costs are necessary for consistency between the two formats.[16] The other cited experiments that also vary the order of the two formats do not find a similar consistency in bidding even in absence of decision support. We think that the consistency in our data stems from the direct comparability of the two formats in our design by using the same price grid and holding opportunity costs constant. Only bidders in the No DSS treatment who start bidding in the FPSBA change their bidding

[15] In order to control for order effects, about half of the participants played in reverse order.

[16] Opportunity costs include, e.g., monitoring costs (Carare and Rothkopf, 2005) or costs from participating in the experiment (Katok and Kwasnica, 2007).



Notes: Depicted are medians of the winning bids for each valuation and format separated by decision support. The reference line is the risk-neutral Nash equilibrium (RNNE) given by Linear SP (L-SP). Participants in No DSS do not receive additional information. In treatment Medium DSS, participants receive information about the winning probability (FPSBA) or the probability to receive the next price (DA). In treatment Full DSS, participants receive the same information as in Medium DSS and, in addition, the expected profit associated with their bid.

Figure 1: Median winning bids across decision support.

behavior and place lower bids when the auction format changes to a DA (SR: $p = 0.0995$). This observation might indicate that, in absence of decision support, the FPSBA is more complex than the DA.

Table 2: Tobit panel regressions of the influence of preferences on winning bids in periods 1 to 18.

	Winning bid			
	(1)	(2)	(3)	(4)
	FPSBA	DA	FPSBA	DA
Valuation	0.523***	0.479***	0.524***	0.479***
	(0.0134)	(0.0154)	(0.0134)	(0.0154)
Allais-type	-0.0222	0.00507	-0.0156	0.00747
	(0.0374)	(0.0289)	(0.0347)	(0.0275)
Risk aversion	6.101**	10.02***	6.202**	9.533***
	(2.974)	(2.983)	(2.754)	(2.928)
Loss aversion	0.488	-0.468	0.441	-0.536
	(0.508)	(0.745)	(0.475)	(0.709)
Numeracy	0.200	-0.469**	0.115	-0.472**
	(0.300)	(0.233)	(0.280)	(0.222)
midDSS			-2.007**	-0.329
			(0.786)	(0.795)
fullDSS			-1.670**	1.218
			(0.812)	(0.753)
Period	0.0865***	0.0336	0.0859***	0.0338
	(0.0237)	(0.0267)	(0.0237)	(0.0267)
Constant	-2.553	-0.00274	-1.005	0.00709
	(2.652)	(2.199)	(2.520)	(2.096)
Observations	443	448	443	448
Participants	41	41	41	41

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Reported are results of tobit panel regressions with an upper limit at the highest possible bid of 21.

5 Conclusion

We examine the role of decision support and preferences in first-price sealed-bid and Dutch auctions. In a laboratory experiment, we elicit participants' preferences and vary the degree of decision support to account for the complexity in deriving the optimal bid. We confirm the frequently observed non-equivalence of the first-price and Dutch auction under the absence of decision support. In addition, we observe that any differences in bidding behavior between the two mechanisms vanish once we provide decision support, which indicates that differences in bidding behavior are due to different levels of complexity. Differences between the two auction formats based on preferences should be independent of the level of decision support. We use the elicited individual preferences of all participants to explain bidding behavior. We find no indication that non-standard preferences explain the empirical differences. Our results thus indicate that the empirical breakdown of equivalence is primarily caused by the complexity of the bidding decision rather than by bidders' preferences. This observation should be taken into account in real-world business interactions involving auctions.

In the experiment, the implemented DSS is perfect in the sense that we can precisely calculate the respective probabilities and expected values due to the fixed bidding strategy of a bidding robot. Obviously, this is not directly implementable in real auctions. However, the availability of historical bid data promotes the design of decision support systems similar to our implementation. Thus, our findings on the differences in auction formats indicate that the higher revenue in the FPSBA is less relevant in real auctions in which bidders are likely to have such support.

References

Abdellaoui, M., H. Bleichrodt, and C. Paraschiv (2007). Loss aversion under prospect theory: A parameter-free measurement. *Management Science 53*(10), 1659–1674.

Adomavicius, G., S. P. Curley, and A. Gupta (2013). Impact of information feedback in continuous combinatorial auctions: An experimental study of economic performance. *MIS Quarterly 37*(1), 55–76.

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'école Américaine. *Econometrica 21*(4), 503–546.

Andreoni, J. and C. Sprenger (2010). Certain and uncertain utility: The Allais paradox and five decision theory phenomena. *Working Paper*.

Anscombe, F. J. and R. J. Aumann (1963). A definition of subjective probability. *Annals of Mathematical Statistics*, 199–205.

Ariely, D. and I. Simonson (2003). Buying, bidding, playing, or competing? Value assessment and decision dynamics in online auctions. *Journal of Consumer Psychology 13*(1&2), 113–123.

Armantier, O. and N. Treich (2009). Star-shaped probability weighting functions and overbidding in first-price auctions. *Economics Letters 104*(2), 83–85.

Beattie, J. and G. Loomes (1997). The impact of incentives upon risky choice experiments. *Journal of Risk and Uncertainty 14*, 155–168.

Belica, M. and K.-M. Ehrhart (2013). Reference-dependent bayesian games. *Working Paper*.

Bichler, M., K. Guler, and S. Mayer (2015). Split-award procurement auctions–can bayesian equilibrium strategies predict human bidding behavior in multi-object auctions? *Production and Operations Management 24*(6), 1012–1027.

Bichler, M., Z. Hao, and G. Adomavicius (2017). Coalition-based pricing in ascending combinatorial auctions. *Infomation Systems Research*.

Bose, S. and A. Daripa (2009). A dynamic mechanism and surplus extraction under ambiguity. *Journal of Economic Theory 144*(5), 2084–2114.

Cai, G. G., P. R. Wurman, and X. Gong (2010, 2014/08/28). A note on discrete bid first-price auction with general value distribution. *International Game Theory Review 12*(01), 75–81.

Camerer, C. F. (1989). An experimental test of several generalized utility theories. *Journal of Risk and Uncertainty 2*, 61–104.

Carare, O. and M. Rothkopf (2005). Slow dutch auctions. *Management Science 51*(3), 365–373.

Cassady, R. (1967). *Auctions and Auctioneering.* University of California Press.

Coppinger, V. M., V. L. Smith, and J. A. Titus (1980). Icentives and behavior in english, dutch and sealed bid auctions. *Economic Inquiry 18*(1), 1–22.

Cox, J. C., B. Roberson, and V. L. Smith (1982). Theory and behavior of single object auctions. *Research in Experimental Economics 2*, 1–43.

Cox, J. C., V. L. Smith, and J. M. Walker (1983). A test that discriminates between two models of the dutch-first auction non-isomorphism. *Journal of Economic Behavior & Organization 4*(2–3), 205–219.

Crawford, V. P. and J. Meng (2011). New york city cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income. *American Economic Review 101*(5), 1912–32.

Dean, M. and P. Ortoleva (2014). Is it all connected? A testing ground for unified theories of behavioral economics phenomena. *Working Paper*.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature 47*(2), 315–372.

Ehrhart, K.-M. and M. Ott (2014). Reference-dependent bidding in dynamic auctions. *Working Paper*.

Eisenhuth, R. and M. Ewers (2012). Auctions with loss averse bidders. *Working Paper*.

Ericson, K. M. M. and A. Fuster (2011). Expectations as endowments: Evidence on reference-dependent preferences from exchange and valuation experiments. *Quarterly Journal of Economics 126*(4), 1879–1907.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 10*(2), 171–178.

Greiner, B. (2015). Subject pool recruitment procedures: Organizing experiments with ORSEE. *Journal of the Economic Science Association 1*(1), 114–125.

Grimm, V. and U. Schmidt (2000). Equilibrium bidding without the independence axiom: A graphical analysis. *Theory and Decision 49*(4), 361–374.

Guler, K., L. Fine, K. Chen, A. Karp, T. Liu, H. Tang, F. Safai, R. Wu, and A. Zhang (2002, November 21). Automated decision support system for designing auctions. US Patent App. 09/858,251.

Guler, K., T. Liu, and H. Tang (2003). Joint estimation of bidders' risk attitudes and private information. US Patent App. 09/904,311.

Guler, K., T. Liu, and H. K. Tang (2009). Method and system for automated bid advice for auctions. US Patent No 7536338.

Haruvy, E. and P. T. L. Popkowski Leszczyc (2009). Internet auctions. *Foundations and Trends in Marketing 4*(1), 1–75.

Hennig-Thurau, T., E. C. Malthouse, C. Friege, S. Gensler, L. Lobschat, A. Rangaswamy, and B. Skiera (2010). The impact of new media on customer relationships. *Journal of Service Research 13*(3), 311–330.

Herweg, F., D. Müller, and P. Weinschenk (2010). Binary payment schemes: Moral hazard and loss aversion. *American Economic Review 100*(5), 2451–2477.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–292.

Katok, E. and A. M. Kwasnica (2007). Time is money: The effect of clock speed on seller's revenue in dutch auctions. *Experimental Economics 11*(4), 344–357.

Kőszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *Quarterly Journal of Economics 121*(4), 1133–1165.

Kim, E. H., A. Morse, and L. Zingales (2006). What has mattered to economics since 1970. *Journal of Economic Perspectives 20*(4), 189–202.

Lange, A. and A. Ratan (2010). Multi-dimensional reference-dependent preferences in sealed-bid auctions –how (most) laboratory experiments differ from the field. *Games and Economic Behavior 68*(2), 634–645.

Lucking-Reiley, D. (1999). Using field experiments to test equivalence between auction formats: Magic on the internet. *American Economic Review 89*(5), 1063–1080.

Nakajima, D. (2011). First-price auctions, dutch auctions, and buy-it-now prices with allais paradox bidders. *Theoretical Economics 6*(3), 473–498.

Savage, L. J. (1954). *The Foundations of Statistics.* John Wiley & Sons, Ltd.

Schmidt, U. and C. Seidl (2014). Reconsidering the common ratio effect: The roles of compound idependence, reduction, and coalescing. *IfW Kiel Working Paper 1930.*

Schwartz, L. M., S. Woloshin, W. C. Black, and G. Welch (1997). The role of numeracy in understanding the benefit of screening mammography. *Annals of Internal Medicine 127*(11), 966–972.

Sprenger, C. (2010). An endowment effect for risk: Experimental tests of stochastic reference points. *Working Paper*.

Turocy, T. L., E. Watson, and R. C. Battalio (2007). Framing the first-price auction. *Experimental Economics 10*(1), 37–51.

Vickrey, W. (1961). Counterspeculation, auctions, and competitive sealed tenders. *Journal of Finance 16*(1), 8–37.

Weber, B. J. (2007). The effects of losses and event splitting on the allais paradox. *Judgment and Decision Making 2*(2), 115–125.

Weber, R. J. (1982). The allais paradox, dutch auctions, and alpha-utility theory. *Northwestern University Discussion Paper 536.*

Zeppenfeld, C. (2015). *Decisions under Uncertainty: Preferences, Institutions, and Social Interaction.* Ph. D. thesis, University of Cologne.

Zhang, B. and K. Guler (2013). Determination of a bid value associated with a selected bidder. US Patent 8,548,882.

A Appendices

A.1 Tables

Table A.1: Tobit panel regression of the influence of preferences and numeracy on differences between winning bids in the FPBSA and the DA in periods 1 to 18.

	Winning Bid
Valuation	0.501***
	(0.0103)
Period	0.0577***
	(0.0181)
Constant	-1.730
	(2.548)
Risk aversion	6.053**
	(2.873)
Loss aversion	0.490
	(0.490)
Allais-type	-0.0225
	(0.0360)
Numeracy	0.216
	(0.290)
DA	0.843
	(3.358)
DA × Risk aversion	3.914
	(4.217)
DA × Loss aversion	-0.937
	(0.913)
DA × Allais	0.0280
	(0.0469)
DA × Numeracy	-0.672*
	(0.377)
Observations	891
Participants	82

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: The upper limit in the Tobit regression is the maximum bid of 21. It was placed in 174 out of 891 observations. DA is a dummy variable that is zero if the auction format is a FPSBA and is one in case of a DA.

Table A.2: Tobit panel regression of the influence of decision support in the FPSBA and the DA in periods 1 to 18.

	Winning bid
Valuation	0.502***
	(0.0103)
Period	0.0581***
	(0.0181)
Constant	1.417
	(1.682)
Allais-type	-0.00370
	(0.0220)
Risk aversion	6.498***
	(1.973)
Loss aversion	0.169
	(0.388)
Numeracy	-0.159
	(0.172)
midDSS	-2.245***
	(0.786)
fullDSS	-1.729**
	(0.815)
DA	-3.251***
	(0.794)
DA × midDSS	2.088*
	(1.131)
DA × fullDSS	3.041***
	(1.130)
Observations	891
Participants	82

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: The upper limit in the Tobit regression is the maximum bid of 21. It was placed in 174 out of 891 observations. DA is a dummy variable that is zero if the auction format is a FPSBA and is one in case of a DA.

Table A.3: Average winning bids for periods 1 to 18.

	No DSS			Medium DSS			Full DSS			KW test	
Valuation	FPSBA	DA	p-value	FPSBA	DA	p-value	FPSBA	DA	p-value	p-value FPSBA	p-value DA
6	4.25	7.42	0.8710	4.25	4.00	0.5541	4.25	3.67	0.4450	0.9905	0.9191
10	6.67	6.00	0.3417	7.31	5.93	0.1234	7.38	6.57	0.6310	0.5114	0.6148
14	10.20	8.35	0.0397	10.38	10.50	0.9575	8.67	8.55	0.7575	0.1396	0.1450
18	14.39	11.04	0.0042	12.57	10.91	0.1105	11.25	11.80	0.1498	0.2347	0.7103
22	15.29	12.05	0.0740	14.54	13.83	0.5108	14.67	13.42	0.2008	0.7910	0.6215
26	18.88	14.50	0.0022	15.18	15.71	0.6428	17.09	17.15	0.8142	0.0150	0.0878
30	19.71	16.14	0.0019	17.96	15.73	0.3084	18.00	18.20	0.786	0.0189	0.1328
34	20.20	17.65	0.0062	18.68	17.04	0.1268	18.83	19.17	0.6750	0.0219	0.1285
38	20.20	17.86	0.0190	19.35	18.42	0.4404	18.50	19.77	0.1287	0.0265	0.1372
Average	15.87	13.33	-	14.57	13.86	-	14.93	15.01	-	-	-

Notes: Reported are the average winning bids for periods 1 to 18 and the probability that bids in the different formats are drawn from the same distribution based on the Wilcoxon-Mann-Whitney U-test. The Kruskal-Wallis (KW) test reports whether there is any significant difference across decision support systems for a given auction format.

A.2 Theory

We consider a situation in which the bidder faces one competitor either in a FPSBA or in a DA. Let $P = \{p_1, p_2, \cdots, p_n\}$ be the common price grid, i.e. the set of possible bids in the FPSBA and the set of possible offers in the DA. Let p_k denote the kth- smallest possible price in this price grid. Let the price grid be uniformly spaced, with $p_k - p_{k-1} = \delta$ for all k.

The probability that the competitor places a bid smaller or equal p_k in the FPSBA is given by $F(p_k)$. $F(p_k)$ also denotes the probability that the highest price offer the competitor is going to accept in a DA is smaller or equal p_k.

For large η and λ the utility of a bidder is mainly driven by the relative outcomes, i.e. by his gain loss utility, and not by absolute outcomes. Consequently, it may be the case that a bidder who has a strictly positive chance of making strictly positive profits and faces no risk of a loss prefers not to participate in the auction. In the following we assume that bidder's expected utility is increasing in his valuation, which rules out such implausible predictions and guarantees monotone bidding functions This assumption is referred to as *no dominance of gain-loss utility* in Herweg et al. (2010).

A.2.1 First-Price Sealed-Bid Auction

In the FPSBA both participants place a bid $b_i \in P$ and the participant who places the higher bid wins. In case of a tie both participants have a winning probability of one half. The expected profit of a bidder with valuation v bidding b_k is given by

$$\begin{aligned} \Pi(b_k, v) &= \left[F(b_{k-1}) + \frac{F(b_k) - F(b_{k-1})}{2}\right] \cdot (v - b_k) && \text{(A.1)} \\ &= \frac{F(b_k) + F(b_{k-1})}{2} \cdot (v - b_k) && \text{(A.2)} \\ &=: P_\omega^k \cdot (v - b_k). && \text{(A.3)} \end{aligned}$$

When relative outcomes are evaluated as

$$\mu(x) := \begin{cases} \eta x & x \geq 0 \\ \eta\lambda x & x < 0, \end{cases} \tag{A.4}$$

the expected utility of a bidder with KR preferences bidding b_k is given by

$$\begin{aligned} U(b_k, v) &= P_\omega^k \cdot (v - b_k) \\ &\quad + P_\omega^k \cdot (1 - P_\omega^k) \cdot \mu(v - b_k) \\ &\quad + P_\omega^k \cdot (1 - P_\omega^k) \cdot \mu(b_k - v) \end{aligned} \tag{A.5}$$

and optimal bids are given by

$$b_{FP}^*(v) = \arg\max_{b \in P} \{U(b, v)\}. \tag{A.6}$$

As the price grid starts at 0, bidders can always place bids smaller their valuation. For this reason the relevant part of the piece-wise defined utility function is given by

$$U(b_k, v) = P_\omega^k \cdot (v - b_k) - P_\omega^k \cdot (1 - P_\omega^k) \cdot (v - b_k) \cdot \eta(\lambda - 1). \tag{A.7}$$

Let v_k be the valuation for which a bidder is indifferent between bidding p_k and p_{k+1}. Given that these v_k are increasing in k the optimal bidding strategy $\beta_{FP}(v)$ is monotone and it is optimal for bidders to bid p_k for all bidders with a valuation between v_{k-1} and v_k. These indifference values are given by

$$U(b_k, v_k) \overset{!}{=} U(b_{k+1}, v_k) \tag{A.8}$$

$$\Leftrightarrow v_k = b_k + \delta \frac{\overbrace{P_\omega^{k+1} - P_\omega^{k+1}(1 - P_\omega^{k+1})\eta(\lambda - 1)}^{:=\Omega_{k+1}}}{\underbrace{P_\omega^{k+1} - P_\omega^k - \eta(\lambda - 1)\left(P_\omega^{k+1}(1 - P_\omega^{k+1}) - P_\omega^k(1 - P_\omega^k)\right)}_{:=\Lambda_k = \Omega_{k+1} - \Omega_k}} \tag{A.9}$$

The *no dominance of gain-loss utility* assumption implies a restriction on values for η and λ:

$$\begin{aligned} & \frac{\partial U(b, v)}{\partial v} = P_\omega^k - P_\omega^k \cdot (1 - P_\omega^k)\eta(\lambda - 1) \overset{!}{\geq} 0 \\ \Leftrightarrow \quad & \eta(\lambda - 1) \overset{!}{\leq} \min_{k \in \{1, \ldots, n\}} \left\{ \frac{1}{1 - P_\omega^k} \right\} \\ \Leftrightarrow \quad & \eta(\lambda - 1) \overset{!}{\leq} \frac{1}{1 - P_\omega^1}, \end{aligned} \tag{A.10}$$

(A.10) implies that $\Omega_k \geq 0$ and $\Lambda_k \geq 0$ for all k and we get

$$\begin{aligned}
v_k - v_{k-1} &= \overbrace{b_k - b_{k-1}}^{=\delta} + \delta \left[\frac{\Omega_{k+1}}{\Lambda_k} - \frac{\Omega_k}{\Lambda_{k-1}} \right] \\
&= \frac{\delta}{\Lambda_k \Lambda_{k-1}} \left[\Lambda_k \Lambda_{k-1} + \Omega_k \Lambda_k - \Omega_{k+1} \Lambda_{k-1} \right] \\
&= \frac{\delta}{\Lambda_k \Lambda_{k-1}} \left[\Lambda_{k-1}(\lambda_k - \Omega_{k+1}) + \Omega_k \Lambda_k \right] \\
&= \frac{\delta \Omega_k}{\Lambda_k \Lambda_{k-1}} \left[\Lambda_k - \Lambda_{k-1} \right] > 0.
\end{aligned}$$

The bidding strategy is then given by

$$\beta_{FP}(v) = \begin{cases} 0 & \text{if } v \in [0, v_1] \\ b_k & \text{if } v \in (v_k, v_{k+1}], \end{cases} \tag{A.11}$$

with $v_{n+1} = 1$ if $v_k \leq 1$. Else if $v_k > 1$ for any k, β_{FP} is adjusted accordingly.

A.2.2 Dutch Auction

In the DA participants sequentially receive decreasing offers $a_j \in P$ starting with p_n. A participant who receives an offer can either accept or reject it. In case of acceptance the auction ends immediately. If the participant who receives the offer p_k first rejects, the other participant will also receive the offer p_k. If the other participant rejects p_k, too, the new offer will be p_{k-1}. Which participant receives the offer p_{k-1} first is randomly determined. This modeling approach is also used by Bose and Daripa (2009).

Every time the bidder receives an offer he has the choice between accepting or waiting for a lower offer. Let H_k be the probability that the bidder will receive an offer p_{k-1} given that he rejects offer p_k. The probability H_k can be split in two parts. First, ρ_k denotes the probability that the price step p_{k-1} is reached, i.e. the probability that the good is not sold at p_k. Second, ϕ_k denotes the probability that the bidder receives an offer p_{k-1} given that the price step p_{k-1} is reached. Consequently, $H_k = \rho_k \cdot \phi_k$.

Computation of ρ_k In order to derive the probability ρ_k of reaching the next price step p_{k-1} we first determine how likely it is that the bidder receives the first offer at p_k given that he receives an offer p_k. First, denote by $\#_k^i \in \{1,2\}$ the position of the bidder in period k. Second, denote by A_k the event that the bidder receives the offer p_k.

$$\Pr\{\#_k = 1|A_k\} = \frac{\Pr\{\#_k = 1\} \cdot \Pr\{A_k|\#_k = 1\}}{\Pr\{\#_k = 1\} \cdot \Pr\{A_k|\#_k = 1\} + \Pr\{\#_k = 2\} \cdot \Pr\{A_k|\#_k = 2\}} \tag{A.12}$$

$$= \frac{\frac{1}{2}}{\frac{1}{2} + \frac{1}{2} \cdot \frac{F(p_k)}{F(p_{k+1})}} \tag{A.13}$$

$$= \frac{F(p_{k+1})}{F(p_{k+1}) + F(p_k)}. \tag{A.14}$$

Consequently, the probability that the bidder is asked second at p_k given that he is asked at p_k is given by

$$\Pr\{\#_k = 2|A_k\} = 1 - \Pr\{\#_k = 1|A_k\} \tag{A.15}$$

$$= \frac{F(p_k)}{F(p_{k+1}) + F(p_k)}. \tag{A.16}$$

Given that the bidder is asked second, $\#_k = 2|A_k$, his rejection of the offer p_k directly implies that the price step p_{k-1} is reached. However, if the bidder is asked first, $\#_k = 1|A_k$, his rejection only implies that the price step p_{k-1} is reached if the competitor also rejects p_k given that she already rejected p_{k+1}, which happens with probability $F(p_k)/F(p_{k+1})$. Hence, the probability ρ_k that price step p_{k-1} will be reached given that the bidder rejects the offer p_k is given by

$$\rho_k = \Pr\{\#_k = 2|A_k\} \cdot 1 + \Pr\{\#_k = 1|A_k\} \cdot \frac{F(p_k)}{F(p_{k+1})} \tag{A.17}$$

$$= \frac{2 \cdot F(p_k)}{F(p_{k+1}) + F(p_k)}. \tag{A.18}$$

Computation of ϕ_k Given that the price step p_{k-1} is reached the probability of being asked first is one half. In this case the bidder receives an offer with certainty. If the opponent is asked first, which also happens with a probability of one half, the bidder receives the item only if the competitor refuses the offer p_{k-1}. The probability that the competitor refuses the offer p_{k-1} given that she refused p_k is given by $F(p_{k-1})/F(p_k)$. Hence, the probability of receiving an offer p_{k-1} given that price step p_{k-1} is reached is given by

$$\phi_k = \frac{1}{2} + \frac{1}{2} \cdot \frac{F(p_{k-1})}{F(p_k)}. \tag{A.19}$$

Computation of H_k Combining the probability ρ_k of reaching the next price step p_{k-1} with the probability ϕ_k of receiving an offer given that the price step p_{k-1} is reached, gives us the probability H_k of receiving another offer when rejecting p_k.

$$H_k = \rho_k \cdot \phi_k \tag{A.20}$$

$$= \frac{F(p_k) + F(p_{k-1})}{F(p_k) + F(p_{k+1})}. \tag{A.21}$$

Bidding Let $\mathrm{R}\left(p_j|p_k\right)$ denote the probability that the bidder will be receive (or has received) an offer p_j given that he is currently offered p_k,

$$\mathrm{R}\left(p_j|p_k\right) := \begin{cases} \frac{F(p_j)+F(p_{j+1})}{F(p_k)+F(p_{k+1})} & j \leq k \\ 1 & j > k. \end{cases} \tag{A.22}$$

Note that for some $a < b < c$,

$$\mathrm{R}\left(a|b\right)\mathrm{R}\left(b|c\right) = \mathrm{R}\left(a|c\right).$$

The expected profit of a bidder with valuation v planning to accept offer p_j who is currently offered $p_k \geq p_j$ is given by

$$\Pi(p_j, v|p_k) = \mathrm{R}\left(p_j|p_k\right) \cdot (v - p_j). \tag{A.23}$$

A bidder with KR preferences conceives a plan at the beginning of the auction, namely accepting the offer $r \in \{p_1, ..., p_m\}$ and evaluates his profit compared to a reference outcome determined by his plan. The utility of such a bidder with valuation v who planned to accept offer r from accepting the current offer p_k is given by

$$u_k = v - p_k + \left(1 - \mathrm{R}\left(r|p_k\right)\right) \cdot \mu\left(v - p_k\right) + \mathrm{R}\left(r|p_k\right) \cdot \mu\left(r - p_k\right). \tag{A.24}$$

Defining

$$u(x, r|y) = v - x + \left(1 - \mathrm{R}\left(r|y\right)\right) \cdot \mu\left(v - x\right) + \mathrm{R}\left(r|y\right) \cdot \mu\left(r - x\right), \tag{A.25}$$

We now analyze two cases:

1. $p_j < r < p_k$**:**

Then, the expected utility from waiting for an offer p_j is given by,

$$U(p_j, v, r|p_k) = R(r|p_k)\Big[(1 - \mathrm{R}(p_j|r))[\mu(r - v)] + R(p_j|r)\,[v - p_j + \mu(r - p_j)]\Big]. \tag{A.26}$$

2. $r < p_j < p_k$**:**

Then, the expected utility from waiting for an offer p_j is given by,

$$U(p_j, v, r|p_k) = R(p_j|p_k)\Big[(1 - \mathrm{R}(r|p_j))[v - p_j + \mu(v - p_j)] + R(r|p_j)\,[v - p_j + \mu(r - p_j)]\Big]. \tag{A.27}$$

The bidder prefers to accept now over waiting if and only if

$$u_{k,r} \geq \max_{p_j < p_k} \{U(p_j, v, r|p_k)\} \tag{A.28}$$

Determining the indifference values $v_{k,r}$ gives us the bidding function,

$$\beta_r(v) = \begin{cases} 0 & \text{if} \quad v \in [0, v_1] \\ \\ p_k & \text{if} \quad v \in (v_k, v_{k+1}], \end{cases} \tag{A.29}$$

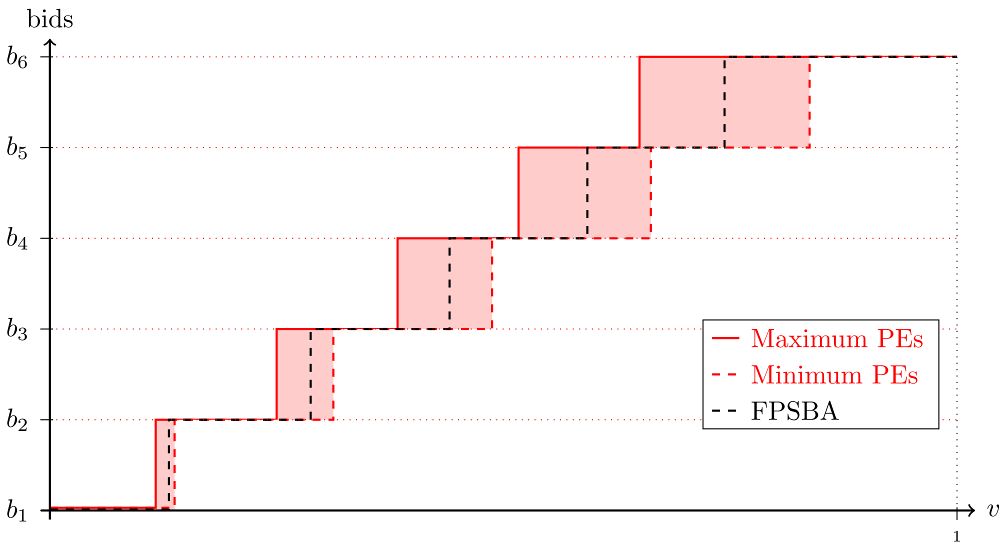
with $v_{m+1} = 1$.

These strategies define best responses to the distribution of competitor's bids $F(x)$. It is easy to see that bidding strategies depend on the reference point r, i.e. the bidders plan when to accept an offer. As a consequence multiple personal equilibria are possible.

A.2.3 First-Price Sealed-Bid Auction vs. Dutch Auction

For subjects with KR preferences it is not possible to make a general statement about the revenue ranking of the FPSBA and the Dutch auction. In the following we provide examples that prove this statement.

Figure A.1: Equilibrium bids in Dutch auctions and FPSBA



Notes: This figure shows the lowest and the highest personal equilibrium bids in the DA and the unique equilibrium bidding strategy in the FPSBA for $\lambda = 2.5$ and $\eta = 0.5$. The revenue ranking of the two auction format depends on the equilibrium selection in the DA.

A.3 Instructions

This section provides the instruction in German (original) and English (translated) separated by parts 1 and 2. Each part consists of part A and part B. Part B was always distributed after part A had been conducted. Experiment 1 was identical for each participant. Experiment 2 was counterbalanced, i.e., half of the participants received the first-price sealed-bid auction in part A followed by the Dutch auction in part B. The other half faced the reversed order. We present the instructions for the full-DSS treatment where subjects had full information. The instructions for the other treatments are the same and only exclude parts of the decision support which is reported in parentheses within the instructions.

Übersicht

Dieser Teil des Experiments besteht aus 18 Runden, die jeweils die gleiche Abfolge an Entscheidungen haben. Am Ende wird eine der 18 Runden zufällig durch den Computer ausgewählt und ausgezahlt. Alle Runden haben dabei die gleiche Wahrscheinlichkeit ausgewählt zu werden.

Erstpreisauktion

Sie nehmen an einer Erstpreisauktion teil, in der Sie ein Produkt erwerben können. Zu Beginn jeder Runde erfahren Sie, welchen Wert das Produkt für Sie hat. Dieser Wert wird aus der Menge

{ 6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 € }

gezogen. Jeder Wert kommt genau zweimal vor. Die Reihenfolge ist jedoch zufällig bestimmt.

Sie befinden sich in einer Gruppe mit einem anderen Bieter. Der andere Bieter ist ein Bietroboter.

In der Auktion kann ein ganzzahliges Gebot zwischen 0 € und 21 € abgegeben werden. Der andere Bieter wählt sein Gebot zufällig zwischen 0 € und 21 €. Jedes Gebot ist dabei gleich wahrscheinlich.

Der Bieter, der das höchste Gebot abgegeben hat, gewinnt die Auktion und erhält das Produkt. Der Preis des Produkts entspricht diesem höchsten Gebot. Falls Sie und der andere Bieter das gleiche Gebot abgeben, erhalten Sie das Produkt mit 50% Wahrscheinlichkeit.

Falls Sie die Auktion gewinnen, ist Ihr Gewinn gegeben durch:

Gewinn = Wert – Gebot.

Falls Sie die Auktion nicht gewinnen, beträgt Ihr Gewinn 0.

Entscheidungshilfe

Bevor Sie Ihr echtes Gebot eingeben, können Sie verschiedene Gebote testen, wofür Ihnen ein Testbereich zur Verfügung steht.

Im Testbereich sehen Sie:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Gewinn, falls Gebot erfolgreich**
  Der Gewinn, falls das aktuelle Testgebot erfolgreich wäre. Dieser wird wie folgt berechnet:
  Gewinn = Wert – Gebot.

[Treatments: Medium DSS, Full DSS]

- **Gewinnwahrscheinlichkeit**
  Die Wahrscheinlichkeit, dass Sie mit einem Gebot in Höhe des Testgebots die Auktion gewinnen.

[Treatments: Full DSS]

- **Erwarteter Gewinn**
  Durchschnittlicher Gewinn, den Sie mit dem Gebot erwarten können. Dieser wird wie folgt berechnet:
  Erwarteter Gewinn = (Gewinnwahrscheinlichkeit) x (Gewinn, falls Gebot erfolgreich).

Gebotsabgabe

- Um Ihr finales Gebot abzugeben, tippen Sie eine Zahl aus der erlaubten Menge der Gebote in das vorgesehene Feld ein. Anschließend klicken Sie auf „Gebot abgeben".
- Sie haben in jeder Runde 60 Sekunden Zeit, Ihr finales Gebot abzugeben. Sollten Sie kein Gebot in den 60 Sekunden abgeben haben, nehmen Sie in dieser Runde nicht an der Auktion teil.

Hinweis

Eine Runde dauert immer 60 Sekunden, unabhängig davon zu welchem Zeitpunkt Sie Ihr Gebot abgegeben haben. Nachdem Sie und der andere Bieter ein finales Gebot abgegeben haben, ist die Auktion zwar beendet, aber die Runde endet erst, wenn die 60 Sekunden abgelaufen sind.

Ergebnis

Übersicht

Dieser Teil des Experiments besteht aus 18 Runden, die jeweils die gleiche Abfolge an Entscheidungen haben. Am Ende wird eine der 18 Runden zufällig durch den Computer ausgewählt und ausgezahlt. Alle Runden haben dabei die gleiche Wahrscheinlichkeit ausgewählt zu werden.

Tickerauktion

Sie nehmen an einer Tickerauktion teil, in der Sie ein Produkt erwerben können. Zu Beginn jeder Runde erfahren Sie, welchen Wert das Produkt für Sie hat. Dieser Wert wird aus der Menge

{ 6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 € }

gezogen. Jeder Wert kommt genau zweimal vor. Die Reihenfolge ist jedoch zufällig bestimmt.

Sie befinden sich in einer Gruppe mit einem anderen Bieter. Der andere Bieter ist ein Bietroboter.

In der Auktion startet der Preis bei 21 € und wird alle 10 Sekunden um 1 € gesenkt. Bei jedem neuen Preis wird zufällig einer der Bieter zuerst gefragt, ob er diesen Preis annehmen möchte. Nimmt der gefragte Bieter den Preis an, so endet damit die Auktion. Lehnt der gefragte Bieter ab, so wird der gleiche Preis dem verbleibenden Bieter angeboten. Beide Bieter haben die gleiche Wahrscheinlichkeit zuerst gefragt zu werden.

Der andere Bieter wählt zufällig einen Preis zwischen 0 € und 21 € aus, zu dem er annehmen würde. Jeder mögliche Preis hat dabei die gleiche Wahrscheinlichkeit ausgewählt zu werden.

Sie gewinnen die Auktion und erhalten das Produkt, falls Sie vor dem anderen Bieter einen Preis annehmen.

Falls Sie die Auktion gewinnen, ist Ihr Gewinn gegeben durch:

Gewinn = Wert – Preis.

Falls Sie die Auktion nicht gewinnen, beträgt Ihr Gewinn 0.

Entscheidungshilfe

Sie sehen auf dem Bildschirm den aktuellen Preis, den nächsten Preis sowie die Zeit bis zum nächsten Preis.

Zusätzlich sehen Sie:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Gewinn bei gegebenem Preis**
  Der Gewinn, falls Sie den Preis annehmen würden. Dieser wird wie folgt berechnet:
  Gewinn bei gegebenem Preis = Wert – Preis.

[Treatments: Medium DSS, Full DSS]

- **Wahrscheinlichkeit, Preis angeboten zu bekommen**
  Die Wahrscheinlichkeit, dass Sie den jeweiligen Preis annehmen können.

[Treatments: Full DSS]

- **Erwarteter Gewinn**
  Durchschnittlicher Gewinn, den Sie erwarten können, wenn Sie sich jetzt entscheiden den jeweiligen Preis anzunehmen. Dieser wird wie folgt berechnet:
  Erwarteter Gewinn = (Wahrscheinlichkeit, Preis angeboten zu bekommen) x (Gewinn, bei gegebenem Preis).

Hinweis

Eine Runde dauert immer 220 Sekunden, unabhängig davon welchen Preis Sie annehmen. Nachdem Sie oder der andere Bieter einen Preis angenommen haben, ist die Auktion zwar beendet, aber die Runde endet erst, wenn die 220 Sekunden abgelaufen sind.

Ergebnis

Nach jeder Runde sehen Sie das Ergebnis der Runde. Hier erfahren Sie den Preis, ob Sie das Produkt erhalten haben und wie hoch Ihr Gewinn ist.

Overview

This part of the experiment consists of 18 rounds which have the same course of decisions. At the end, one of the 18 rounds will be randomly selected by the computer and paid out. All rounds have the same probability to be selected.

First-Price Auction

You will participate in a first-price auction in which you can acquire a product. At the beginning of each round, you will learn which value this product has for you. The value will be drawn from the set

{6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 €}.

Each value occurs exactly twice. The order, however, is random.

You are in a group with one other bidder. This other bidder is a bidding robot.

In the auction, you can enter an integer bid between 0 € and 21 €. The other bidder will choose his bid randomly between 0 € and 21 €. Every bid is equally likely.

The bidder with the highest bid wins the auction and receives the product. The price of the product is given by this highest bid. If you and the other bidder submit the same bid, you have a 50% chance to receive the product.

If you win the auction, your profit is given by:

Profit = Value – Bid.

If you do not win the auction, your profit is 0.

Decision Support

Before you enter your actual bid, you can test different bids for which a testing area is provided for you.

In the testing area, you will see:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Profit if bid was successful**
  The profit if the actual profit was successful. It is calculated as follows:
  Profit = Value – Bid.

[Treatments: Medium DSS, Full DSS]

- **Winning Probability**
  The probability that you win the auction with a bid equal to the test bid.

[Treatments: Full DSS]

- **Expected Profit**
  Average profit that you can expect with the bid. It is calculated as follows:
  Expected Profit = (Winning Probability) x (Profit if bid is successful).

Bid Submission

- To submit your final bid, type in a number out of the feasible set of bids into the respective field. Then, click on "submit bid".
- In each round, you have 60 seconds to submit your final bid. If you do not submit a bid within these 60 seconds, you will not participate in the auction in this round.

Note

One round always lasts for 60 seconds, independently of when you submit your bid. After you and the other bidder submitted a final bid, the auction end but the round will only end after the 60 seconds have elapsed.

Result

After each round, you will see the result of that round. Here you learn the price, whether or not you received the product, and how large your profit is.

Overview

This part of the experiment consists of 18 rounds which have the same course of decisions. At the end, one of the 18 rounds will be randomly selected by the computer and paid out. All rounds have the same probability to be selected.

Ticker Auction

You will participate in a ticker auction in which you can acquire a product. At the beginning of each round, you will learn which value this product has for you. The value will be drawn from the set

{6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 €}.

Each value occurs exactly twice. The order, however, is random.

You are in a group with one other bidder. This other bidder is a bidding robot.

In the auction, the price starts at 21 € and will decrease by 1 € every 10 seconds. At every new price, one of the bidders is randomly asked whether or not he wants to accept the price. If the bidder accepts the price, the auction ends. If the bidder rejects the price, the same price is offered to the remaining bidder. Both bidders have the same probability to be asked first.

The other bidder will randomly choose a price a price between 0 € and 21 € which he would accept. Each feasible price has the same probability to be chosen.

You will win the auction and receive the product if you accept a price before the other bidder does.

If you win the auction, your profit is given by:

Profit = Value – Bid.

If you do not win the auction, your profit is 0.

Decision Support

On your screen, you see the current price, the next price, and the time until the next price is shown.

In addition, you will see:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Profit at given price**
  The profit if you accepted the current price. It is calculated as follows:
  Profit at given price = Value – price.

[Treatments: Medium DSS, Full DSS]

- **Probability to be offered the given price**
  The probability that you can accept the respective price.

[Treatments: Full DSS]

- **Expected Profit**
  Average profit that you can expect if you decide now to accept the respective price. It is calculated as follows:
  Expected Profit = (Probability to be offered this price) x (Profit at given price).

Note

One round always lasts 220 seconds, independently of which price you accept. After you or the other bidder accepted a price, the auction ends but the round will only end after the 220 seconds have elapsed.

Result

After each round, you will see the result of that round. Here you learn the price, whether or not you received the product, and how large your profit is.

A.4 Screens in the lab experiment

Notes: Depicted is the computer interface used in the first-price sealed-bid auction. The individual valuation is depicted at the very top. Participants have a test button *Test-Gebot* (*Test bid*) that allows to enter a bid. Depending on the decision support, the following information is calculated from the test bid: *Profit falls Test-Gebot erfolgreich* (*Profit if bid was successful*) (No, Medium, and Full DSS), *Gewinnwahrscheinlichkeit* (*Winning probability*) (Medium and Full DSS), and *Erwarteter Profit* (*Expected profit*) (Full DSS). A timer displays the remaining time to submit a real bid that can be entered in the text field in the lower right corner and submitted by pressing the button *Gebot abgeben* (*Submit bid*).

Figure A.2: Computer Interface: FPSBA.

Notes: Depicted is the computer interface used in the Dutch auction. The individual valuation is depicted at the very top. The screen shows the current price, the time until the next price, and the next price. Depending on the decision support, the following information is calculated automatically: *Gewinn bei gegebenem Preis* (*Profit at given price*) (No, Medium, and Full DSS), *Wahrscheinlichkeit, Preis angeboten zu bekommen* (*Probability to be offered the given price*) (Medium and Full DSS), and *Erwarteter Gewinn* (*Expected profit*) (Full DSS). The current price can be accepted by pressing the button *Preis annehmen* (*Accept price*).

Figure A.3: Computer Interface: DA.