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Understanding preferences for ascending auctions, Buy-It-Now auctions and fixed prices

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Abstract

This paper experimentally analyzes how consumers decide between entering a fixed price, an ascending auction or a BIN auction. We find that such entry decisions depend both on potential payoffs (price aspects) and consumer characteristics (non-price aspects). For values smaller than or equal to BIN prices, subjects are more likely to enter a mechanism that involves bidding. Conversely, for values greater than BIN prices, subjects are more likely to enter a mechanism that involves immediate buying. We further find that price aspects mainly play a role for values greater than BIN prices, whereas non-price aspects play a role for values smaller than or equal to BIN prices. Impatience makes subjects less likely to enter a mechanism involving bidding, whereas sensation seekingness and regret make subjects more likely to enter such a mechanism. Gender also has an impact on entry decisions.

Keywords: Entry decisions, Fixed price, Ascending auction, Buy-It-Now auction

JEL classification: C91, D44

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1. Introduction

The rise in popularity of Internet retailing has led to increased diversity in selling mechanisms. Besides buying commodities at a fixed price, consumers may also participate in one of many online auctions. Online auctions are used to sell a wide variety of commodities—from electronics and collector’s items in online marketplaces to holidays and concert tickets in specialized online auction stores—and many different auction formats are used to do so. Recently, online auctioneers have introduced fixed price features in their auctions through the use of Buy-It-Now (BIN) options. In auctions with such a BIN option consumers can bid for a commodity, but can additionally choose to end the auction by buying the commodity at a fixed price. Both eBay and Yahoo—two of the most successful online marketplaces—currently offer three types of selling mechanisms: fixed price, ascending auction and BIN auction. This diversity in selling mechanisms allows consumers to choose not only from which seller, but even in which type of selling mechanism to buy.

A recent line of research studies how consumers make such entry decisions between selling mechanisms. More specifically, it investigates how consumers choose between entering an auction or taking up an outside option (Engelbrecht-Wiggans, 1993; Levin and Smith, 1994; Smith and Levin, 1996), or between several auction formats (Ivanova-Stenzel and Salmon, 2004, 2008a,b, 2011; Engelbrecht-Wiggans and Katok, 2005). Understanding how consumers decide which selling mechanism to enter is of interest to sellers who are striving to increase revenue. After all, in a market in which commodities are sold in competing mechanisms, attracting many consumers is of utmost importance as this not only increases the likelihood to sell at a fixed price, but also drives up the price in auctions (Krishna, 2002). Consider a consumer who wants to buy a single commodity and can choose from several selling mechanisms. How does she decide which mechanism to enter? The literature offers two explanations.

First, consumers may decide to enter a selling mechanism based on the payoff that this mechanism potentially provides. In auction theory it is typically assumed that payoffs are equal to consumers’ values for the commodity, minus the corresponding payment. Payoffs may be difficult to predict in auctions—especially when considering non-standard auctions and bidders who do not use risk neutral Nash equilibrium (RNNE) bidding strategies—but researchers have found that consumers’ values by themselves have a strong impact on entry decisions. Menezes and Monteiro (2000) find in a theoretical model of endogenous entry into auctions that only consumers with values greater than a certain cut-off decide to enter the auction. In an experiment, Ivanova-Stenzel and Salmon (2011) find that consumers with lower values decide to enter first price auctions more often, whereas consumers with higher values more often decide to enter ascending auctions.

Second, entry decisions may be affected by the format of the selling mechanism itself. After all, consumers are heterogeneous in their attitudes and psychological traits, which may result in heterogeneous preferences over mechanisms. Palfrey and Pevnitskaya (2008), for instance, find theoretical and experimental evidence that only more risk tolerant consumers choose to enter auctions, whereas more risk averse consumers choose not to. Ivanova-Stenzel and Salmon (2004, 2008a,b) find in a series of experiments that the ascending auction is preferred to the first price auction. They find that this may be explained by risk aversion as reflected in consumers’ bidding behavior, but not by loss aversion or aversion to the dynamic bidding process. According to Engelbrecht-Wiggans and Katok (2007), regret may also explain this preference. These consumer characteristics, and with them many more, might all play a role in entry decisions.

The present study provides experimental evidence on how consumers choose to enter a selling mechanism versus an alternative mechanism. Can such entry decisions simply be explained by potential payoffs (price aspects), or do consumer characteristics (non-price aspects) also play a role? To answer this question our exploratory experiment involves subjects making a series of entry decisions between three selling mechanisms: fixed price, ascending auction and BIN auction. These three mechanisms are not only empirically relevant, but are also sufficiently strategically different, which may lead consumers to have preferences over these mechanisms. We include a number of psychometric measures in the experiment, which together constitute the non-price aspects. These measures involve a risk attitude elicitation task, a loss attitude elicitation task, and a questionnaire measuring impatience, sensation seeking and regret.

Our results show that entry decisions depend both on price and non-price aspects. Potential payoffs,

defined as consumers' values minus the price of the BIN option, play an important role in entry decisions. For values smaller than or equal to BIN prices, subjects are more likely to enter a mechanism that involves bidding. Conversely, for values greater than BIN prices, they are more likely to enter a mechanism that involves immediate buying. We further find that price aspects mainly play a role for values greater than BIN prices, whereas non-price aspects play a role for values smaller than or equal to BIN prices. Impatience makes subjects less likely to enter a mechanism involving bidding, whereas sensation seekingness and regret make subjects more likely to enter such a mechanism. Furthermore, we find that gender is an important factor in explaining entry decisions.

Our study is related to two strands of literature: the literature on bidder preferences and entry into auctions, which was already briefly discussed, and the literature on BIN auctions. Whereas there is a vast literature dealing with BIN auctions, the issue of endogenous entry is not yet applied to these auctions. Some studies have considered a consumer's decision to bid or to buy within BIN auctions (Angst et al., 2008; Budish and Takeyama, 2001; Reynolds and Wooders, 2009; Tan et al., 2005), but none have looked at the decision between entering a BIN auction or an alternative mechanism. A study closely related to ours is that of Sun et al. (2010), who examine which selling mechanism—fixed price, ascending auction or BIN auction—generates most revenue to sellers. They show theoretically that the answer depends on the interaction between bidders' costs to participate in an auction and sellers' costs to hold on to a commodity in case it is not sold. Our study can be considered as complementary to Sun et al. (2010). That is, in a market in which commodities are sold through a variety of mechanisms and consumers may choose to enter any of them, attracting as many consumers as possible has a positive effect on expected seller revenues in both fixed price and auctions. Moreover, seller revenues may be affected not only by the number of consumers a certain mechanism attracts, but even by the type of consumers it attracts. Examining entry decisions over fixed price, ascending auction and BIN auction, may thus provide more insights into which mechanism will generate most revenue to sellers.

The remainder of this paper is structured as follows. Section 2 describes the design and procedures of our experiment. Section 3 contains a description of our sample and the results of the analysis of our data. Section 4 discusses our findings and provides concluding remarks.

2. Experimental design and procedures

Our experimental design aimed at studying entry decisions between three selling mechanisms. It followed to some extent the methods used by Ivanova-Stenzel and Salmon (2004, 2008a,b, 2011), but was modified in several ways. Section 2.1 explains how the three selling mechanisms are played, Section 2.2 describes the psychometric measures and Section 2.3 describes the procedures of the experiment.

2.1. Selling mechanisms

The experiment involved subjects playing three types of selling mechanisms: fixed price, ascending auction and BIN auction. In each selling mechanism a single unit of a fictitious commodity was sold. The value of this commodity was drawn independently for each subject from a uniform distribution with support $[0,100]$.³ If a subject won the commodity, she received a payoff equal to her value minus her payment. If a subject did not win the commodity, she received a payoff of zero. Mechanisms were run in continuous time, meaning that subjects had 45 seconds to win the commodity. Each mechanism had different rules defining the actions subjects could take, and determining the winner and payment.

In the fixed price, the commodity could be bought at a fixed, posted price by using the BIN option. This BIN price was randomly drawn from a uniform distribution with support $[0,100]$. The first subject to use the BIN option won and paid the BIN price. In case both subjects did not use the BIN option within 45 seconds, both received a payoff of zero. In case both subjects used the BIN option simultaneously, the winner of the commodity was randomly determined.⁴

³All values are denoted in experimental currency units (ECU).

⁴Because mechanisms were run in continuous time and the BIN option was permanently available in both the fixed price and the BIN auction, this never happened during our experiment.

The ascending auction allowed subjects to place multiple bids. The bidding process in our experiment therefore differed from that of previous research (Ivanova-Stenzel and Salmon, 2004, 2008a,b, 2011). Whereas in most previous work the ascending auction is in fact a Japanese or ascending clock auction⁵, we allowed subjects to place bids themselves, where bids were restricted to integer values between 0 and 150. As a consequence, bidding strategies may have involved jump bidding and last minute bidding. The subject with the highest bid after 45 seconds won and paid a price equal to the winning bid.

In the BIN auction, subjects could bid for the commodity according to the rules of the ascending auction, but could additionally buy it immediately at the BIN price. The BIN option was permanently available and subjects could choose to end the auction at any time. If the BIN option was never used, the rules of the ascending auction dictated the winner: the subject with the highest bid won and paid her own highest bid. If the BIN option was used, the rules of the fixed price dictated the winner: the first subject to use the BIN option won and paid the BIN price.

Throughout the experiment subjects faced only one competitor in each mechanism, i.e. $n=2$. Not only did this maximize the number of observations while keeping the number of subjects limited, it also eliminated entry coordination.⁶ This means that subjects had no incentive to enter a mechanism with the sole purpose of trying to be the only one choosing this mechanism and, hence, win with certainty. An alternative design would have been to offer two commodities in two simultaneously running mechanisms, like Ivanova-Stenzel and Salmon (2008a, 2011) do. In this case, subjects need not only take into account potential payoffs and their preferences, but also need to consider the number of subjects that will enter the same mechanism.

2.2. Psychometric measures

We chose to elicit five consumer characteristics during the experiment. The measures involved a risk attitude elicitation task, a loss attitude elicitation task, and a questionnaire measuring impatience, sensation seeking and regret. Some of these were chosen based on findings in previous literature discussed in Section 1, such as risk attitudes (Palfrey and Pevnitskaya, 2008; Ivanova-Stenzel and Salmon, 2004, 2008a,b) and regret (Engelbrecht-Wiggans and Katok, 2007). Others we chose to include because we believe they may play a role not only for entry decisions in general, but especially for the mechanisms in our experiment, such as impatience and loss attitudes.

Attitudes towards risk were measured using the method introduced by Holt and Laury (2002), which consists of a sequence of ten paired lottery choices each time involving a safe payment and a risky payment. Both lotteries have a high and a low payoff, where the high (low) payoff of the risky lottery is higher (lower) than that of the safe lottery. In the first paired lottery choice the high payoff is reached with a probability of 0.10. This probability increases with 0.10 in each paired lottery choice, until the high payoff is reached with certainty in the last paired lottery choice. A subject's attitude towards risk then determines at which paired lottery choice she switches from the 'safe' lottery to the 'risky' lottery. Subjects were informed that, after all subjects made all ten decisions, only one of these was selected at random and played to determine her earnings.

As an alternative measurement for attitudes towards risk, we used the thrill and adventure seeking (TAS) subscale of Zuckerman (1994) Sensation Seeking Scale V (SSSV). This subscale examines the subject's appeal to dangerous activities or risk taking, and has been shown to correlate significantly with behavior towards risk (Rosenkranz and Weitzel, 2012; Zaleskiewicz, 2001; Zuckerman and Kuhlman, 2000). The data were gathered using a questionnaire containing 10 forced choice items.

Attitudes towards loss were measured using a method similar to that of Gächter et al. (2010). In our experiment, subjects faced six decisions in which they could either accept or decline a lottery. Each lottery

⁵In Japanese or ascending clock auctions the price starts at zero and increases gradually until a maximum of 150. This process continues until one of the bidders indicates that she is withdrawing from the auction, with the remaining bidder winning the auction at the price at which the other bidder dropped out.

⁶Even though we kept the number of competitors in each mechanism fixed, our experiment still involved a coordination problem. That is, subjects may not only consider their own potential payoffs and preferences in their entry decisions, but may also consider the potential payoffs and preferences of their competitors, as this could influence bidding strategies and, hence, prices.

involved a 0.50 probability of winning 125 ECU, and a 0.50 probability of losing an amount ranging from 25 ECU to 150 ECU. A subject's degree of loss aversion affects which lotteries she declines. Again, only one of the subject's choices was selected at random and played to determine her earnings.

Impatience was measured by conducting the Monetary Choice Questionnaire by Kirby et al. (1999). In this questionnaire subjects had to make 27 hypothetical decisions between receiving an smaller, immediate monetary reward and a larger, delayed monetary reward.

The Regret Scale of Schwartz et al. (2002), consisting of five statements, was used to assess subjects' tendency to experience regret. Subjects responded to these statements using a seven-point Likert-scale ranging from 0 (completely disagree) to 6 (completely agree).

A description of the tasks and questionnaires used to compute the psychometric measures during the experiment, can be found in Appendix D in Tables D1 to D5.

2.3. Procedures

Six sessions, with 132 subjects, were run in the experimental laboratory ELSE at Utrecht University in June 2012. Participating subjects came from the subject pool that mainly recruits students of Utrecht University from all faculties and study programmes (ORSEE, Greiner (2004)). The procedures during the sessions were kept constant and all sessions were computerized using the software z-Tree (Fischbacher, 2007). ELSE has 30 cubicles and connected PCs allowing computer-assisted exchange of information. At the start of the experiment, subjects were seated in random order at the computers in the laboratory. During the sessions, they were not allowed to communicate. The instructions (see Appendix A), available in Dutch and English, were printed and read individually. Questions about the instructions were answered in private by the experimenter. Sessions lasted approximately 90 minutes, including instructions, psychometric measures and a final questionnaire.

Following Ivanova-Stenzel and Salmon (2004, 2008a,b, 2011), the experimental design consisted of two phases. In the first phase, which is referred to as the learning phase, subjects participated in several rounds of mechanisms, which allowed them to determine their strategies and form preferences over the mechanisms. At the start of each round, a subject was randomly matched to another subject. Subjects did not know the identity of the other subject in their pair, neither during the experiment nor after. Each pair received a randomly determined BIN price, which was the same for both fixed price and BIN auction, and all subjects received independent private values. Subjects then participated in three trading periods, where fixed price, ascending auction and BIN auction were each played once and the subject pairs, values and prices were kept constant. The order in which the mechanisms were played was randomly determined and varied across sessions. After three trading periods a new round commenced, in which subjects were paired with a new subject, received a new value and a new BIN price. In total, subjects participated in four rounds, resulting in 12 trading periods in the learning phase for which they received real earnings. At the end of the learning phase subjects received information on their total earnings so far.

In the second phase, the choice phase, subjects faced a series of entry decisions. Nine choice tasks were presented, in which subjects had to choose multiple times between entering one of two mechanisms: fixed price versus ascending auction, fixed price versus BIN auction, and ascending auction versus BIN auction. In each choice task subjects received a list of ten randomly drawn values for which they had to decide which mechanism to enter. Before making this decision, subjects were informed about the BIN price, which was randomly drawn and constant for all subjects in the session. After all subjects reached a decision, one of the ten choices made by the subject was picked at random and was then actually played. Subjects knew that, regardless of their choice, they would always compete against one other subject. In case a certain mechanism was entered by an odd number of subjects, one of the subjects was placed in a mechanism by default. This was classified as a mismatch, and the identity of this subject was randomly decided. For each pair of mechanisms subjects received three choice tasks, resulting in 30 entry decisions per pair of mechanisms and nine trading periods in the choice phase. Again, the order in which the choice tasks were presented was randomly determined and varied across sessions.

After both phases finished, subjects were informed about their earnings so far. They would then take part in some additional decision tasks, during which they did the risk assessment and the loss assessment.

Table 1: Summary Statistics

	N	Mean	SD	Min	Max
1. Gender ¹	114	0.561	0.498	0	1
2. Age	114	23.158	3.769	17	43
3. Nationality ²	114	0.605	0.491	0	1
4. Students ³	114	0.877	0.330	0	1
5. Economics ⁴	114	0.333	0.473	0	1
6. Mechanism Profits	114	312.465	132.989	28	664
7. Nr. of Losses	114	0.289	0.634	0	3
8. Impatience	114	-5.056	2.018	-10.820	-0.693
9. Risk Attitude	114	6.272	1.576	1	9
10. Loss Attitude	114	5	1.234	1	7
11. Sensation Seeking	114	6.439	2.380	0	10
12. Regret	114	16.404	6.349	0	29

¹ Female=1, male=0.

² Dutch=1, non-Dutch=0.

³ Student=1, non-student=0.

⁴ Economics student=1, other=0.

Afterwards they were informed about their final earnings and were asked to answer a questionnaire on personal data and online auction experience. This questionnaire also included the SSSV-TAS, the Monetary Choice Questionnaire and the Regret Scale. Earnings were converted to Euro at an exchange rate of 25 ECU = €1, and were rounded up to 50 cents. Subjects that could not participate in the experiment received a show-up fee of €3.00.

3. Results

The experiment was conducted with 132 subjects. Due to missing values, we were unable to include the data of 16 subjects as some subjects made inconsistent choices in the risk and/or loss assessment. The data of two other subjects were excluded because multiple questionnaire items were answered inconsistently, and because their experimental results were significantly different from the rest of the group. Our final sample consists of 114 subjects. On average, these subjects earned €16.08⁷, with a minimum of €3.00 and a maximum of €33.50.

3.1. Sample description

Table 1 provides a summary of our data. Variables 1 to 5 describe the general population of our subjects. Roughly 56% of our subjects were female, 61% had the Dutch nationality and on average they were 23 years old. A majority of our subjects were students (88%) and one third studied economics.

The variables in the second part of Table 1 summarize subjects' performances in the experiment. On average, subjects earned 312 ECU by trading, both in the learning phase and in the choice phase. Since our experimental design allowed subjects to overbid and to buy at BIN prices higher than their values, some subjects made losses during the experiment. Even though some subjects made up to three losses, the majority of subjects (79%) made no losses at all. An overview of the performance of the various selling mechanisms can be found in Table C1 in Appendix C. This Appendix also provides additional information on subjects' bidding and buying behavior during the experiment, as well as a discussion on how this affected performance measures such as average bidder surplus, revenue and efficiency.

The third part of Table 1 describes the psychometric variables measured during the experiment. Subjects' responses to the Monetary Choice Questionnaire are transformed into discount rates using a technique introduced by Wileyto et al. (2004). Impatience is then recorded as the natural log of these discount

⁷The average earnings of all 132 subjects were €15.61. Two subjects made an overall loss (of -€5.00 and -€3.50, respectively), but nevertheless received the show-up fee of €3.00. Subjects were not aware of this show-up fee and were warned about making losses in the instructions. The two subjects who made an overall loss were not included in the final sample due to missing values.

Table 2: Frequency table considering entry decisions.

	All Data		Value \leq Price		Value $>$ Price	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
Fixed Price	1338	39.12%	102	6.75%	1236	64.75%
Ascending Auction	2082	60.88%	1409	93.25%	673	35.25%
Fixed Price	877	25.64%	121	6.32%	756	50.27%
BIN Auction	2543	74.36%	1795	93.68%	748	49.73%
Ascending Auction	1721	50.32%	1272	74.34%	449	26.27%
BIN Auction	1699	49.68%	439	25.66%	1260	73.73%

rates, which is on average -5.056. This corresponds to a discount rate of 0.0064 and indicates a relative lack of discounting and a preference for delayed rewards. Using the method of Holt and Laury (2002), risk attitudes are classified into nine risk categories, ranging from highly risk loving to extremely risk averse. The subjects in our experiment are on average risk averse. Loss attitudes range from 1 (accept all lotteries) to 7 (reject all lotteries). On average, subjects accept all lotteries up to the point where potential gains equal potential losses. This suggests that subjects are on average neutral towards losses. Sensation Seeking scores (Cronbach's alpha of 0.679) may range from 0 to 10 points, with 10 being highly sensation seeking. Subjects in our experiment have on average lower scores (6.439) than the normative sample from Zuckerman (1994) (7.01), when corrected for the ratio of women and men. This is consistent with our finding that subjects are on average risk averse. Regret scores are taken from the Regret Scale (Cronbach's alpha of 0.804) and may range from 0 to 30, with 30 being highly sensitive to feelings of regret. On average our subjects seem to be only somewhat sensitive to feelings of regret.

Table B1 in Appendix B reports the pairwise correlations of the variables described in Table 1.

3.2. Entry decisions

Our experiment required subjects to choose between entering one mechanism versus an alternative mechanism. This entry decision is the main interest of our analysis, and is recorded as a binary variable where 0 represents a subject choosing one mechanism and 1 represents the subject choosing an alternative mechanism. We study whether and how these entry decisions are affected by price and non-price aspects. Potential payoffs are used as a proxy for price aspects. As potential payoffs in auctions may be difficult to calculate—it is difficult for subject to predict the winning bid—we choose to measure potential payoffs as the difference between subjects' values and BIN prices. Hence, we restrict attention to the potential payoffs of choosing the BIN option. In the remainder of this paper we therefore refer to the potential payoffs of the BIN option when using the term potential payoffs. Non-price aspects are represented by impatience, risk attitudes, loss attitudes, sensation seeking and regret, and are measured in the way described in Section 3.1. Because in each choice task subjects had to choose between two mechanisms, most of our analysis deals with each pair of mechanisms separately.

An overview of how often a certain mechanism is chosen can be found in Table 2. We find that subjects choose to enter fixed price less often than the ascending auction or the BIN auction. There is virtually no difference in entry frequencies for the choice between ascending auction and BIN auction. To study these entry decisions more in-depth, we divide our data in two sets. The first set consists of entry decisions for which values are smaller than or equal to BIN prices. For these values using the BIN option would never generate positive payoffs; only bidding could lead to positive payoffs. This means that potential payoffs for fixed price are zero at best. The second set consists of entry decisions for which values are greater than BIN prices. For these values both bidding and buying may generate positive payoffs. Table 2 shows that there is quite some difference in entry frequencies between the two sets.

Result 1. *Potential payoffs significantly affect entry decisions. For values smaller than or equal to BIN prices, the majority of subjects decide to enter a mechanism that involves bidding. For values greater than BIN prices, the majority of subjects decide to enter a mechanism that involves buying.*

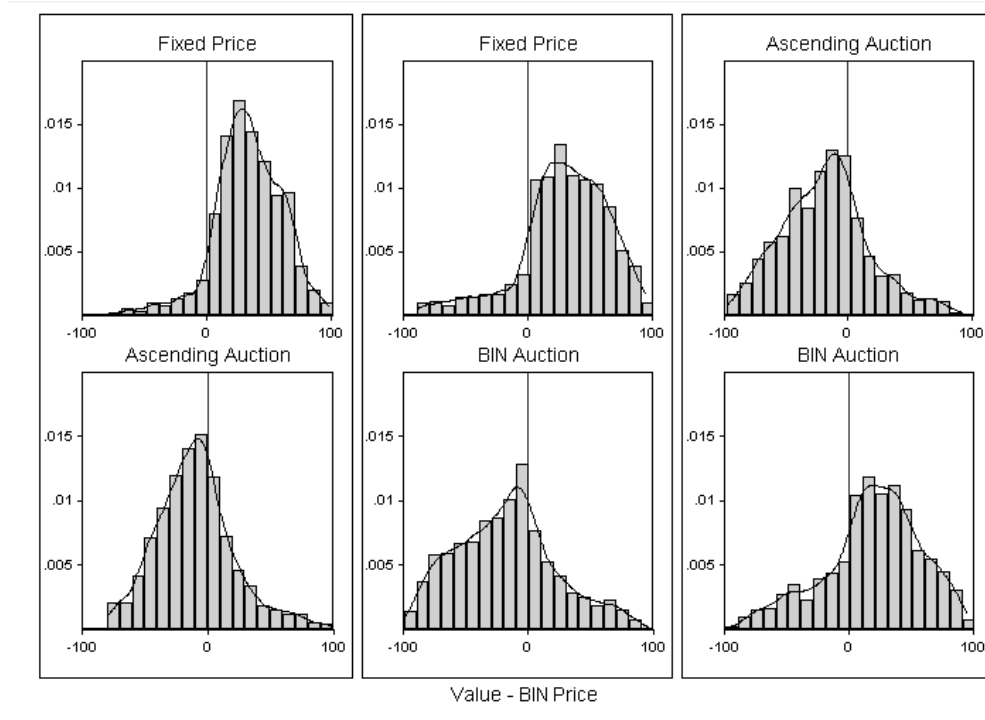


Figure 1: Distribution plots of the difference between values and BIN prices of subjects choosing a certain mechanism. Each column refers to a different pair of mechanisms.

Chi-square tests confirm that the difference in entry frequencies between the two sets is significant. This is true for all pairs of mechanisms: fixed price and ascending auction ($\chi^2(1, N=3420) = 1.2e+03, p = 0$), fixed price and BIN auction ($\chi^2(1, N=3420) = 853.602, p = 0$), and ascending auction and BIN auction ($\chi^2(1, N=3420) = 790.294, p = 0$). For values smaller than or equal to BIN prices, most subjects prefer to enter ascending auction over fixed price and BIN auction, and prefer to enter BIN auction over fixed price. Conversely, for values greater than BIN prices, most subjects prefer to enter fixed price over ascending auction, and prefer to enter BIN auction over ascending auction. A graphical depiction of Result 1 is shown in Figure 1, which displays the distribution plots of the potential payoffs of subjects choosing a certain mechanism.

In Table 3, entry decisions for all pairs of mechanisms are combined into a single variable: preference rankings. These rankings were constructed by ordering preferences⁸ over mechanisms for each subject individually. Table 3 provides additional evidence for Result 1. The preference rankings show that, for values smaller than or equal to BIN prices, a majority of subjects (92%) prefer the two auctions over the fixed price. For values greater than BIN prices, preferences are quite heterogeneous. Whereas half of the subjects (51%) prefer the fixed price and the BIN auction to the ascending auction, we also find that many subjects have intransitive⁹ preferences.

To gain further insight into how entry decisions are made, we examine choice behavior on an individ-

⁸In this case, showing a preference for a mechanism means that a subject must choose this mechanism at least once more than the alternative mechanism. When using a different criterion (e.g. requiring that a subject chose a mechanism at least 75%) results do not change significantly.

⁹Subjects' preferences were coded as intransitive if we were unable to construct a ranking. However, this does not necessarily mean that these subjects indeed have intransitive preferences, as it may also be the result of strategic interaction in the experiment or an expression of indifference between mechanisms.

Table 3: Preference ranking

Preference ranking	Value \leq Price		Value $>$ Price	
	Freq.	Percent	Freq.	Percent
FP \succ A \succ BIN	1	0.88%	1	0.88%
FP \succ BIN \succ A	1	0.88%	33	28.95%
FP \succ A \sim BIN	0	0.00%	7	6.14%
A \succ FP \succ BIN	1	0.88%	0	0.00%
A \succ BIN \succ FP	77	67.54%	11	9.65%
A \succ FP \sim BIN	1	0.88%	0	0.00%
BIN \succ FP \succ A	1	0.88%	20	17.54%
BIN \succ A \succ FP	19	16.67%	6	5.26%
BIN \succ FP \sim A	0	0.00%	8	7.02%
FP \sim A \sim BIN	0	0.00%	0	0.00%
FP \sim A \succ BIN	1	0.88%	1	0.88%
FP \sim BIN \succ A	1	0.88%	5	4.39%
A \sim BIN \succ FP	9	7.89%	5	4.39%
Intransitive	2	1.75%	17	14.91%

ual level. We find that some subjects have a strong bias towards one of the mechanisms. For the choice between fixed price and ascending auction, only one of 114 subjects exclusively chose fixed price, whereas six exclusively chose ascending auction. For the choice between ascending auction and BIN auction we observe similar numbers: five subjects exclusively chose ascending auction and six exclusively chose BIN auction. Surprisingly, for the choice between fixed price and BIN auction as many as 38 subjects exclusively chose BIN auction. This finding, combined with subjects' behavior in the mechanism itself—only 5% of the BIN decisions are made after observing at least one bid—suggests that the BIN auction is used more as an alternative to fixed price than as a hybrid mechanism in which subjects only buy after a certain threshold has been reached.

Individual choice behavior also shows that many subjects follow a cut-off strategy. At potential payoffs below some cut-off value, say x , subjects choose one mechanism (typically one that involves bidding). At potential payoffs above some cut-off value, y , subjects choose another mechanism (typically one that involves buying). Figure 2 shows, for each pair of entry decisions, that most subjects switch once between mechanisms, indicating that for these subjects $x=y$. A substantial number of subjects also switches three times between mechanisms, indicating that they are indifferent between mechanisms for a range of potential payoffs.

Result 2. *Most subjects use a cut-off strategy when making entry decisions.*

Surprisingly, there seems to be a difference in the way females and males decide which mechanism to enter. Using Mann-Whitney-Wilcoxon tests, adjusted for tied ranks, we find that among the subjects who switch at least once, females switch significantly less often than males. This is true for all three pairs of mechanisms (fixed price and ascending auction ($z=3.493$, $p<0.01$), fixed price and BIN auction ($z=3.319$, $p<0.01$), and ascending auction and BIN auction ($z=3.347$, $p<0.01$)) and indicates that females are more likely to follow a strict cut-off strategy than males.

Result 3. *Gender significantly affects entry decisions. For values smaller than or equal to BIN prices, females are more likely than males to decide to enter a mechanism that involves bidding. For values greater than BIN prices, females are more likely than males to decide to enter a mechanism that involves buying.*

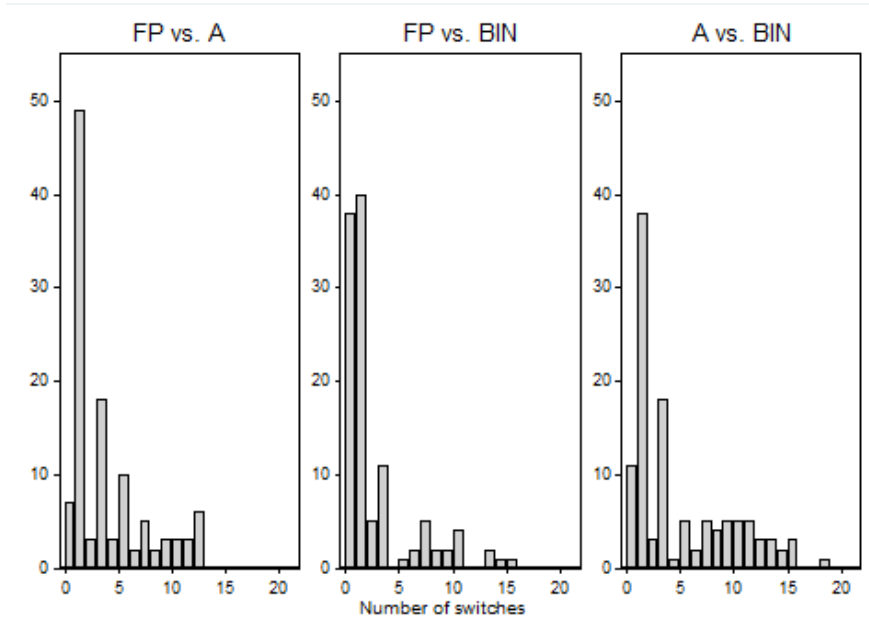


Figure 2: Number of times subjects switch between mechanisms.

We find further evidence for this result by studying entry decisions with the use of regression analysis. We investigate the impact of potential payoffs, gender and the psychometric variables¹⁰ on entry decisions, which are coded as a binary variable. Table 4 shows the results of random effects logit panel regressions. The regressions are conducted for each pair of mechanisms separately: columns (I), (II) and (III) only consider fixed price versus ascending auction, columns (IV), (V) and (VI) only consider fixed price versus BIN auction, and columns (VII), (VIII) and (IX) only consider ascending auction versus BIN auction.

For every specification, we first report the results for all entry decisions, in columns (I), (IV) and (VII). Apart from entry decisions between ascending auction and BIN auction, there do not seem to be major differences in the way subjects choose between mechanisms. Potential payoffs have a statistically significant effect (at one percent) on all entry decisions. This again confirms Result 1. For larger differences between values and BIN prices, subjects are more likely to enter fixed price than ascending auction or BIN auction, and are more likely to enter BIN auction than ascending auction. Furthermore, we find evidence confirming Result 3, as gender has a statistically significant (at one percent) negative effect in columns (I) and (IV). When choosing between entering the fixed price and ascending (BIN) auction, females are less likely than males to enter the ascending (BIN) auction. For entry decisions between ascending auction and BIN auction, we find no effect of gender. Impatience also has an effect on entry decisions, but only for those decisions in which subjects choose between entering the ascending auction and an alternative mechanism (columns (I) and (VII), with $p < 0.05$ and $p < 0.01$ respectively). As the ascending auction is the only mechanism that will always last 45 seconds—it cannot be ended early by using the BIN option—we find that impatient subjects are less likely to enter this mechanism.

Result 4. *Impatience has a negative effect on the likelihood of entering an ascending auction.*

To study how entry decisions are made in more detail, we again divide our data into two sets. Columns (II), (V) and (VIII) report the results for values smaller than or equal to BIN prices. Columns (III), (VI) and

¹⁰We also controlled for other factors, such as subjects' earnings in the mechanism in the learning phase and nationality. Neither of these variables were found to be significant, however, and were therefore removed from the final regressions.

(IX) report the results for values greater than BIN prices. Making this distinction immediately shows why gender was not statistically significant in column (VII): gender has a statistically significant (at five percent) negative effect in column (VIII) and a statistically significant (at one percent) effect in column (XI). More specifically, for values smaller than or equal to BIN prices we find that females are more likely than males to enter the ascending auction, whereas for values greater than BIN prices they are more likely to enter the BIN auction. This is in accordance with our observation that females are more likely to follow strict cut-off strategies.

By dividing the data into two sets, we also find that there is quite some contrast in the way subjects make entry decisions for different potential payoffs. Whereas for values greater than BIN prices only potential payoffs and gender are statistically significant (columns (III), (VI) and (IX)), for values smaller than or equal to BIN prices the psychometric variables mainly play a role (columns (II), (V) and (VIII)).

Result 5. *Whereas entry decisions mainly depend on price aspects for values greater than BIN prices, entry decisions are driven by non-price aspects for values smaller than or equal to BIN prices.*

Sensation seekingness has a statistically significant effect in all entry decisions for values smaller than or equal to BIN prices (at five percent in columns (II), at ten percent in column (V) and at one percent in column (VIII)). For entry decisions in this set, subjects cannot receive a positive payoff by using the BIN option. This means that in fixed price they can do nothing but wait. In the BIN auction these subjects can still place bids, but it is possible that the commodity will be bought immediately by their competitor. For these potential payoffs, we therefore find that highly sensation seeking subjects are more likely to enter ascending auction or BIN auction than fixed price, and are more likely to enter ascending auction than BIN auction. That is, these subjects enter a mechanism that involves bidding rather than a mechanism that involves buying.

Result 6. *Sensation seekingness has a positive impact on the likelihood of entering a mechanism that involves bidding.*

Risk attitudes only have an effect on entry decisions in certain situations. In column (II) and column (VIII), risk attitudes are statistically significant (at ten percent), meaning that more risk averse subjects are more likely to enter the ascending auction than the fixed price or the BIN auction. Surprisingly, these effects move in the opposite direction of Result 6. Although previous research (e.g. Zaleskiewicz, 2001) has shown that the thrill and adventure seeking subscale of the SSSV is related to risk attitudes, we do not find a significant correlation between the two (see Table B1 in Appendix B). The effect of loss attitudes on entry decisions is insignificant in all specifications.

Result 7. *Whereas loss attitudes never significantly affect entry decisions, the effect of risk attitudes is only occasionally significant.*

Finally, we observe that regret has a statistically significant (at ten percent in column (VII) and at one percent in column (VIII)) negative effect on the decision between entering the ascending auction and the BIN auction. Engelbrecht-Wiggans and Katok (2007) argue that ascending auctions are regret-free. In the fixed price or BIN auction, however, subjects may experience regret in case they want to buy at the BIN price but their competitor is slightly faster and wins the commodity. Therefore, we find that subjects who are more sensitive towards feelings of regret are more likely to enter the ascending auction than the BIN auction.

Result 8. *Regret has a positive effect on the likelihood of entering the ascending auction rather than the BIN auction.*

4. Conclusion

This study investigates entry decisions between three selling mechanisms. Buying at a fixed price and bidding in an ascending auction are compared to a third mechanism which combines the two: the BIN auction. The results of our exploratory experiment show that both price and non-price aspects play a role in entry decisions.

Entry decisions heavily depend on potential payoffs, which in our analysis are defined as the difference between values and BIN prices. For values smaller than or equal to BIN prices, subjects are more likely to enter a mechanism that involves bidding. For values greater than BIN prices, subjects are more likely to enter a mechanism that involves buying immediately. We further find that price aspects mainly play a role for values greater than BIN prices, whereas non-price aspects play a role for values smaller than or equal to BIN prices. Our results show that impatience has a negative impact on the likelihood of entering a mechanism that involves bidding, whereas sensation seeking and regret have a positive impact on the likelihood of entering such a mechanism. Surprisingly, we also find that gender is an important factor in explaining entry decisions. Females are more likely than males to use strict cut-off strategies in their entry decisions. Furthermore, they are more likely than males to enter a mechanism involving bidding for values smaller than or equal to BIN prices, and more likely to enter a mechanism involving buying for values greater than BIN prices.

These findings suggest that sellers should take into account how potential consumers' entry decisions may be affected by the mechanism selected, since the format of the mechanism itself will affect how many and which types of consumers enter a certain selling mechanism. This, in turn, may have an effect on seller revenues.

In general, our findings are consistent with the literature on entry decisions into auctions. We confirm the use of cut-off strategies in entry decisions, as was demonstrated by Ivanova-Stenzel and Salmon (2011). Additionally, we confirm that entry decisions are affected by regret (Engelbrecht-Wiggans and Katok, 2007), but not by loss attitudes (Ivanova-Stenzel and Salmon, 2008b). The impact of risk attitudes on entry decisions, however, is unclear. Both Palfrey and Pevnitskaya (2008) and Ivanova-Stenzel and Salmon (2004, 2008a,b) show that risk attitudes play a role in entry decisions. On the one hand, our findings show that risk attitudes, as elicited in the Holt and Laury (2002) task, have no clear-cut effect on entry decisions. On the other hand, we find that sensation seekingness makes subjects more likely to enter a mechanism involving bidding. To the extent that sensation seekingness may serve as a measure for risk attitudes, this matches the findings from Palfrey and Pevnitskaya (2008). That is, more risk tolerant (sensation seeking) subjects choose to enter the auctions instead of an outside option (fixed price).

It is surprising that when risk attitudes, as measured by the Holt and Laury (2002) elicitation task, do have an effect, it moves in the opposite direction of the effect of sensation seekingness. Moreover, we do not find a statistically significant correlation between the two. A first explanation for this may be that the predictive validity of expected utility-based assessments of risk attitudes is questionable when decisions concern low stakes (Harrison et al., 2005), as is the case in our experiment. A second explanation for the opposite effects is based on the experimental design decisions made in our study. In the real world, choosing to buy at a fixed price is not nearly as risky as in our experimental design. In the literature, this is reflected in the assumption that buying at a fixed price is completely safe. The outside option in the study of Palfrey and Pevnitskaya (2008), for instance, is a certain payoff that subjects receive when they decide not to participate in the auction. However, from an experimental point of view, it was important that selecting the BIN option would give the same result in fixed price as in the BIN auction. In both cases, the subject that selected the BIN option first won the commodity. For this reason, the level of risk in fixed price and BIN auction is similar, and it is then perhaps not a surprise that risk attitudes are often insignificant. Sensation seekingness, on the contrary, does not directly measure risk taking propensity, but rather measures personality traits associated with risk taking. These traits may play a role in entry decisions independent of risk attitudes.

Future research may examine whether the findings in our experiment are robust to changes in the experimental design. An interesting extension to our research would be to allow more than two subjects to compete in a mechanism and, hence, allow for entry coordination. By allowing for such coordination,

subjects do not only need to consider their own potential payoffs and preferences, but also need to take into account the number of competitors they might encounter after entering a certain mechanism. The results of this exercise may then provide insights into which mechanism generates the highest revenue to sellers and with this add to existing literature on revenue ranking.

Table 4: Random effects panel regressions examining entry decisions between fixed price and ascending auction (where 0=FP and 1=A), fixed price and BIN auction (where 0=FP and 1=BIN), and ascending auction and BIN auction (where 0=A and 1=BIN).

	Fixed price vs. Ascending auction			Fixed price vs. BIN auction			Ascending auction vs. BIN auction		
	(I)	V ≤ P (II)	V > P (III)	(IV)	V ≤ P (V)	V > P (VI)	(VII)	V ≤ P (VIII)	V > P (IX)
Value – BIN Price	-0.0594*** (0.00221)	0.00195 (0.00856)	-0.0508*** (0.00382)	-0.0503*** (0.00229)	-0.00427 (0.00559)	-0.0492*** (0.00482)	0.0379*** (0.00157)	0.00825** (0.00389)	0.0388*** (0.00393)
Gender	-0.868*** (0.310)	0.833 (0.985)	-1.827*** (0.511)	-1.781*** (0.628)	0.465 (1.065)	-4.159*** (1.063)	0.593 (0.375)	-2.013** (0.926)	1.828*** (0.556)
Impatience	-0.167** (0.0701)	-0.443* (0.262)	-0.104 (0.113)	-0.205 (0.140)	-0.401 (0.269)	-0.197 (0.236)	0.254*** (0.0865)	0.813*** (0.229)	0.174 (0.128)
Risk attitude	0.144 (0.0976)	0.552* (0.310)	0.113 (0.160)	0.312 (0.193)	0.147 (0.329)	0.422 (0.331)	-0.199* (0.119)	0.0609 (0.298)	-0.261 (0.174)
Loss attitude	-0.146 (0.124)	0.0188 (0.375)	-0.305 (0.202)	-0.170 (0.251)	0.183 (0.427)	-0.329 (0.411)	0.133 (0.150)	-0.215 (0.378)	0.0603 (0.221)
Sensation seeking	0.0526 (0.0624)	0.488** (0.219)	-0.0497 (0.102)	0.0413 (0.127)	0.412* (0.228)	-0.169 (0.207)	-0.140* (0.0764)	-0.552*** (0.193)	-0.0121 (0.112)
Regret	0.0117 (0.0223)	0.0234 (0.0675)	0.0209 (0.0365)	-0.0238 (0.0444)	-0.0581 (0.0761)	0.00375 (0.0740)	-0.0454* (0.0271)	-0.241*** (0.0713)	-0.0259 (0.0394)
Constant	0.293 (1.084)	-3.103 (3.685)	1.913 (1.762)	1.703 (2.193)	2.063 (3.867)	3.781 (3.624)	3.126** (1.322)	9.847*** (3.412)	2.267 (1.973)
Observations	3,420	1,511	1,909	3,420	1,916	1,504	3,420	1,711	1,709
Number of Subject	114	114	114	114	114	114	114	114	114
LL	-1386	-203.7	-832.4	-1050	-221.8	-518.0	-1589	-500.5	-678.0
Prob > chi2	0	0.347	0	0	0.534	0	0	6.91e-05	0

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Appendix

A. Instructions

You are participating in an economics experiment. Please read the following instructions carefully. These instructions state everything you need to know in order to participate in the experiment, and they are identical for all participants in the experiment. If you have any questions, please raise your hand. One of the experimenters will approach you in order to answer your question. You can earn money by means of earning points during the experiment. The number of points that you earn depends on your own choices and the choices of other participants. At the end of the experiment, the total number of points that you earn during the experiment will be exchanged at an exchange rate of:

$$25 \text{ points} = \text{€ } 1$$

The money you earn will be paid out anonymously and in cash at the end of the experiment. The other participants will not see what you earn. Further instructions on this will follow below and on the computer screen. During the experiment you are not allowed to communicate with other participants and you are

not allowed to use your cell phone. Also, you may only use the functions of the PC necessary for the experiment.

Overview of the experiment

The experiment will consist of two phases. After reading this set of instructions, you will receive instructions for phase 1 and this phase will start. After completing the first phase, you will be handed a new set of instructions for phase 2. After completing both phases, you will be asked to participate in some short additional decision making tasks and to fill in a questionnaire. In this set of instructions you can find general information about the experiment.

In this experiment you can earn points by participating in a series of games or mechanisms. In each mechanism you will compete with one other participant to earn points. Only one of you can win these points. If you are the winner, you will receive a payoff which is equal to your value (which is given to you by the computer) minus the price (which is determined differently in each mechanism). Note that this payoff may also be negative. For example, if you have a value of 40 and a price of 25, you will earn 15 points. Likewise, if you have a value of 25 and a price of 40, you will earn -15 points. If you lose, you will receive no points. Thus, the number of points you can earn in a mechanism is:

If you win:	value - price
If you lose:	0

During the experiment you will remain anonymous. You will not get to know the identity of the other participant in your pair, neither during the experiment nor after the experiment. The other participants will also not know your identity.

Value

For you and for each other participant the computer separately draws a value from the interval [0,100], where each value is equally likely. You are informed only about your own private value and have no information on the values of the other participants. Note that your value does not provide any information on the values of the other participants, since values are randomly drawn from the interval [0, 100] for each participant separately.

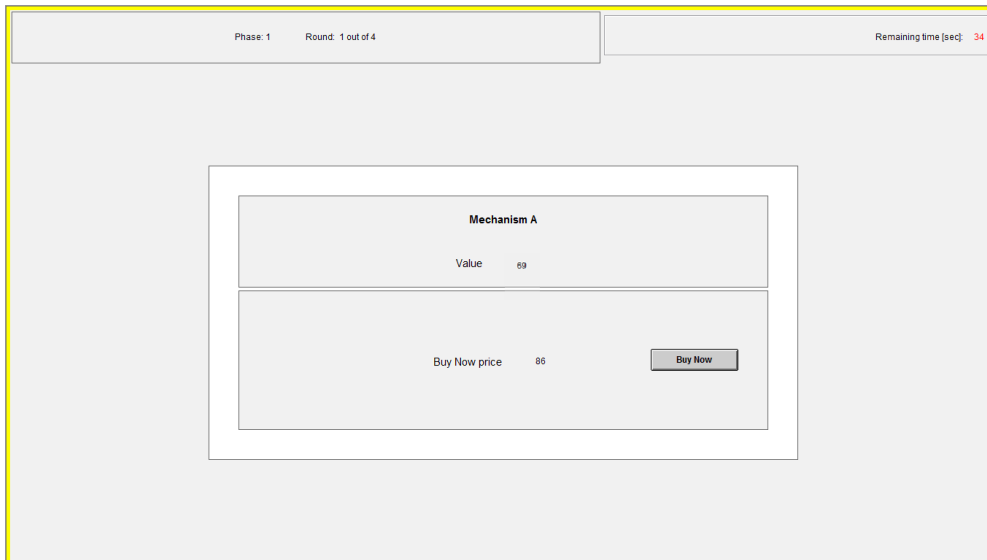
Mechanisms

In each mechanism the rules for winning are different. Furthermore, the price is determined differently in each mechanism. In some mechanisms you have the opportunity to influence the price, whereas in others you cannot. You always have 45 seconds to choose your actions, which determine both whether you win or lose and the price you have to pay. On the following pages these mechanisms are explained in more detail. Please make yourself familiar with these mechanisms and keep these descriptions next to your computer, so that you can check them if necessary.

Mechanism A

In mechanism A you can win points by pushing a Buy Now button. The first participant in your pair to push the Buy Now button will win and earn a payoff equal to his or her value, minus some fixed price. This fixed price is set by the computer and is between 0 and 100. If the price is higher than the winner's value he or she receives a negative payoff. Thus, in some instances it may be better not to attempt to win. In case both participants push the Buy Now button simultaneously, the winner will be picked randomly. If no participant pushes the Buy Now button within 45 seconds, both players lose and receive no points.

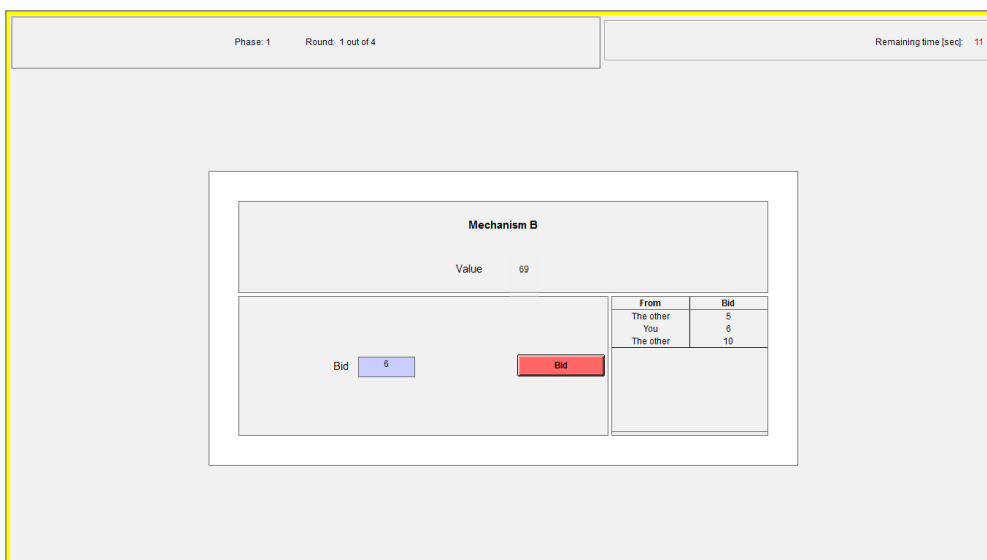
On the screen you can see your current value, the Buy Now price, the phase and round you are currently in and the time remaining for you to make your choice. In order to make sure you have enough time to inspect your value and the Buy Now price, you can only push the button after 3 seconds. The time remaining is shown in the upper right corner of the screen.



Mechanism B

In mechanism B you have the opportunity to influence the price the winner pays, by placing bids. During 45 seconds, you and the other participant are allowed to place bids, which may be any number from 0 up to 150 and can only include integer values (1, 2, ..., 150). You can only place a bid that is at least 1 point higher than the previous bid. After 45 seconds, the participant with the highest bid will be the winner and pays a price equal to his or her highest bid. If no participant ever places a bid, none of the participants will receive points.

On the screen you can again see your current value, the phase and round you are currently in and the time remaining to place your bids. Additionally, you can see the bidding history of you and the other participant and the current highest bid. Again, you can only start bidding after 3 seconds.



Mechanism C

In mechanism C the computer again sets a fixed price between 0 and 100. You can either choose to accept this fixed price by pushing the Buy Now button or to set the price yourself by placing bids. Again, you are only allowed to place a bid between 0 and 150 (1, 2, ..., 150) and bids should be at least 1 point higher than the most recent bid. As soon as any participant pushes the Buy Now button, this participant will win and the mechanism ends. If no participant pushes the Buy Now button within 45 seconds, the participant with the highest bid wins and pays a price equal to his or her highest bid. If no participant ever pushes the Buy Now button or places a bid, none of the players will receive points.

On the screen you can see your current value, the Buy Now price, the phase and round you are currently in and the remaining time. At any time, you see on the screen all of the previous bids, including your own previous bids and those of the other participant. You can only start bidding or push the Buy Now button after 3 seconds.

The screenshot shows the 'Mechanism C' interface. At the top, it displays 'Phase: 1' and 'Round: 3 out of 4' on the left, and 'Remaining time [sec]: 15' on the right. The main area contains a box with the following elements:

- Mechanism C** title
- Value:** 88
- Bid:** A text input field containing '5' and a red 'Bid' button.
- Buy Now price:** 34 and a grey 'Buy Now' button.
- Bid History Table:**

From	Bid
You	1
The other	2
You	5
The other	11

Phase 1

In the first phase you will participate in a series of mechanisms. You will participate in four rounds. In each round of this phase you will play three mechanisms (mechanism A, B and C), which will be presented in varying order. At the start of each round you will be informed of your value and the Buy Now price. You will be randomly matched with one other participant in each round, so it is likely that you will compete with a different participant each time. After you have played all three mechanisms a new Buy Now price, value and participant to which you are paired will be selected and the new round begins. At the conclusion of this phase you will be informed about your total points earned so far.

Phase 2

In this phase you will encounter nine different choice tasks. In every choice task you will be asked to choose between two mechanisms. You will have to choose three times between mechanisms A and B, three times between A and C, and three times between B and C. The order in which these choice tasks are presented is varied. A single choice task will look as follows.

Phase 2 Task: 9 out of 9

Choice Task - Buy Now price 47

Values	Please choose between the two mechanisms	
8	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
19	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
28	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
33	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
46	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
50	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
55	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
68	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
97	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>
99	Mechanism A <input type="radio"/>	Mechanism B <input type="radio"/>

In every choice task you will receive a list of ten randomly drawn values that you may potentially have, and for each value you are asked to choose between the two mechanisms. During the choice task you can see the Buy Now price on the screen, which you will have to pay if you push the Buy Now button in mechanism A or mechanism C. The Buy Now price is chosen by the computer and is the same for all participants. All participants face the same choices. After all participants have indicated their choices, each participant is randomly assigned one of the values in his or her list. You will then play the mechanism of your choice for this value, with a participant that has chosen the same mechanism. If it is not possible to find a participant with the same preference, you may not end up playing the mechanism of your choice. This is done in order to ensure that everyone participates in a mechanism. Finally, the chosen mechanism is played in exactly the same way as in phase 1. After this has been completed, you will receive a new choice task between two mechanisms with a new random Buy Now price and a new list of ten values, and where the choice task proceeds as before.

B. Summary statistics

Table B1: Pearson correlations

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Gender ¹	-											
2. Age	0.037	-										
3. Nationality ²	-0.063	-0.052	-									
4. Students ³	0.046	-0.533***	0.026	-								
5. Economics ⁴	-0.016*	-0.402***	-0.305***	0.265***	-							
6. Mechanism Profits	-0.032	0.048	0.144	0.012	-0.030	-						
7. Nr of Losses	0.069	-0.071	-0.198**	-0.082	0.059	-0.442***	-					
8. Impatience	0.145	-0.093	-0.318***	0.044	0.172*	-0.203**	0.304***	-				
9. Risk Attitude	0.345***	-0.018	-0.077	-0.003	-0.158*	-0.068	0.107	0.151	-			
10. Loss Attitude	0.288***	-0.099	-0.015	0.065	-0.061	-0.049	0.102	0.078	0.355***	-		
11. Sensation Seeking	-0.262***	-0.226**	-0.010	0.035	0.199**	-0.001	-0.044	0.067	-0.115	-0.241***	-	
12. Regret	0.040	0.008	-0.028	-0.103	0.014	-0.049	-0.038	-0.039	-0.023	0.099	-0.195**	-

*** p<0.01, ** p<0.05, * p<0.1

¹ Female=1, male=0.

² Dutch=1, non-Dutch=0.

³ Student=1, non-student=0.

⁴ Economics student=1, other=0.

C. Behavior and performance

To get an idea of subjects' bidding and buying behavior and how this affects performance measures, we take a closer look at the mechanisms played during the experiment. Table C1 provides an overview of the performance of the various selling mechanisms in the experiment. Non-parametric statistical tests are used to check for significant differences between the mechanisms.

Table C1: Performance measures

	Times played†	Avg Bidder Surplus ¹	Revenue ²	Efficiency ³
<i>Learning Phase</i>				
Fixed Price	197	9.556	28.898	0.513
Ascending Auction	197	17.985	25.015	0.736
BIN Auction	197	16.586	26.178	0.675
<i>Choice Phase</i>				
Fixed Price	51	20.529	32.882	0.588
Ascending Auction	91	12.890	23.253	0.780
Fixed Price	30	20.450	27.767	0.500
BIN Auction	114	11.140	28.447	0.754
Ascending Auction	71	15.732	27.380	0.915
BIN Auction	74	18.122	30.851	0.608

† Games in which one of the bidders was forced into the mechanism were excluded from consideration.

¹ Average bidder surplus is measured as the winner's payoff divided by the number of bidders in the mechanism.

² Revenue is measured as the price paid in the mechanism.

³ Efficiency is measured as the percentage of mechanisms that is won by the subject with the highest value.

Kruskal-Wallis tests are conducted to evaluate differences between the outcomes in the learning phase. The tests, corrected for tied ranks, show that average bidder surplus ($\chi^2(2, N=591) = 54.806, p = 0.0001$) and efficiency ($\chi^2(2, N=591) = 22.793, p = 0.0001$) differ significantly between mechanisms. Revenue does not differ significantly between mechanisms in the learning phase ($\chi^2(2, N=591) = 0.932, p = 0.6275$). To evaluate pairwise differences between the three mechanisms we conduct post-hoc tests, controlling for Type I error across tests by using a Bonferroni correction. Mann-Whitney tests reveal significant differences between fixed price and the other mechanisms for average bidders surplus (FP vs. A ($z = -6.764, p = 0$); FP vs. BIN ($z = -5.910, p = 0$)) and efficiency (FP vs. A ($z = -4.571, p = 0$); FP vs. BIN ($z = -3.279, p = 0.001$)). We do not find significant differences between ascending auction and BIN auction for both average bidder surplus ($z = 1.289, p = 0.1973$) and efficiency ($z = 1.325, p = 0.1853$).

Using Mann-Whitney tests, we find that efficiency is significantly different between all mechanisms (FP vs. A ($z = -2.413, p = 0.0158$); FP vs. BIN ($z = -2.699, p = 0.0069$); A vs. BIN ($z = 4.309, p = 0$)) in the choice phase. We further find that average bidder surplus is significantly higher in fixed price than in ascending auction ($z = 4.096, p = 0$) and BIN auction ($z = 3.740, p = 0.0002$), but not significantly different between the two auctions ($z = -1.054, p = 0.2917$). This is not surprising, as fixed price is almost exclusively entered by subjects with values higher than BIN prices, therefore leading to higher potential payoffs than in the alternative mechanism. Finally, revenue is significantly higher in fixed price than in ascending auction ($z = 3.067, p = 0.0022$). No significant differences are found between fixed price and BIN auction ($z = -0.875, p = 0.3818$), or ascending auction and BIN auction ($z = 0.075, p = 0.9400$).

Subjects' buying behavior in fixed price is very fast: 92% of all buys are made within 5 seconds. After all, the fixed price has a strong first-come, first-served nature. The fastest subject to select the BIN option wins and takes it all. The first-come, first-served nature of the fixed price has turned this mechanism into a game of skill, which may explain a level of efficiency close to 50%. Furthermore, because of the existence of a positive BIN price, in fixed price a commodity may not be sold even though consumers may have a positive value for it. Indeed, we find that if subjects cannot opt out of the mechanism, as is the case in the learning phase, nothing will be sold in 27% of all trading periods. This is in line with the lower average bidder surplus for this mechanism in the learning phase reported in Table C1.

In the ascending auctions we observe both jump bidding and last minute bidding. On average, each subject submits 1.86 bids. The majority (53%) of winning bids are placed within less than 5 seconds of the end of the auction. These bidding strategies may explain the rather low level of efficiency (78%)—in

ascending auctions without a fixed deadline, such as the classic English auction, efficiency levels close to 99% are not unusual.

Finally, in the BIN auction we observe fast buying decisions as well as jump bidding and last minute bidding. Overall, in 54% of all BIN auctions subjects bought at the BIN price. Interestingly, we observe that if subjects exercise the BIN option this is often done immediately. Only 6% of all BIN decisions are made after observing at least one bid.

D. Psychometric measures

Table D1: Risk attitude elicitation task based on Holt and Laury (2002)

Task						Measure			
Option A		Option B		Expected payoff* difference	Safe choices [†]	Risk classification	Freq.	Percent	
50	40	96.25	2.5						
1	1/10	9/10	1/10	9/10	29.125	0-1	1. Highly risk loving	1	0.88%
2	2/10	8/10	2/10	8/10	20.750	2	2. Very risk loving	0	0%
3	3/10	7/10	3/10	7/10	12.375	3	3. Risk loving	4	3.51%
4	4/10	6/10	4/10	6/10	4.000	4	4. Risk neutral	12	10.53%
5	5/10	5/10	5/10	5/10	-4.375	5	5. Slightly risk averse	15	13.16%
6	6/10	4/10	6/10	4/10	-12.750	6	6. Risk averse	27	23.68%
7	7/10	3/10	7/10	3/10	-21.125	7	7. Very risk averse	30	26.32%
8	8/10	2/10	8/10	2/10	-29.500	8	8. Highly risk averse	18	15.79%
9	9/10	1/10	9/10	1/10	-37.875	9-10	9. Extremely risk averse	7	6.14%
10	10/10	0/10	10/10	0/10	-46.250				

* Payoffs are given in ECU, where 25 points = €1.

[†] Attention is restricted to consistent choices.

Table D2: Loss attitude elicitation task based on Gächter et al. (2010)

Task				Measure			
	Lottery		Expected payoff*	Lotteries rejected [†]	Loss classification	Freq.	Percent
	1/2	1/2					
1	-25	125	50	0	1. Accept all	2	1.75%
2	-50	125	37.5	1	2. Accept 1-5/Reject 6	3	2.63%
3	-75	125	25	2	3. Accept 1-4/Reject 5-6	7	6.14%
4	-100	125	12.5	3	4. Accept 1-3/Reject 4-6	21	18.42%
5	-125	125	0	4	5. Accept 1-2/Reject 3-6	35	30.70%
6	-150	125	-12.5	5	6. Accept 1/Reject 2-6	40	35.09%
				6	7. Reject all	6	5.26%

* Payoffs are given in ECU, where 25 points = €1.

[†] Attention is restricted to consistent choices.

Table D3: Money Choice Questionnaire (Kirby et al., 1999)

Option A	Option B
€54 today	€55 in 117 days
€55 today	€75 in 61 days
€19 today	€25 in 53 days
€31 today	€85 in 7 days
€14 today	€25 in 19 days
€47 today	€50 in 160 days
€15 today	€35 in 13 days
€25 today	€60 in 14 days
€78 today	€80 in 162 days
€40 today	€55 in 62 days
€11 today	€30 in 7 days
€67 today	€75 in 119 days
€34 today	€35 in 186 days
€27 today	€50 in 21 days
€69 today	€85 in 91 days
€49 today	€60 in 89 days
€80 today	€85 in 157 days
€24 today	€35 in 29 days
€33 today	€80 in 14 days
€28 today	€30 in 179 days
€34 today	€50 in 30 days
€25 today	€30 in 80 days
€41 today	€75 in 20 days
€54 today	€60 in 111 days
€54 today	€80 in 30 days
€22 today	€25 in 136 days
€20 today	€55 in 7 days

Table D4: Thrill and adventure seeking subscale of Sensation Seeking Scale V (Zuckerman, 1994)

Statement A	Statement B
1 I often wish I could be a mountain climber.	I can't understand people who risk their necks climbing mountains.
2 (r) A sensible person avoids activities that are dangerous.	I would like to try to do things that are a little frightening.
3 I would like to take up the sport of water skiing.	I would not like to take up the sport of water skiing.
4 I would like to try surfing.	I would not like to try surfing.
5 (r) I would not like to learn to fly an aeroplane.	I would like to learn to fly an aeroplane.
6 (r) I prefer the surface of the water to the depth.	I would like to go scuba diving.
7 I would like to try parachute jumping.	I would never want to try jumping out of a plane.
8 I like to dive off the high board.	I don't like the feeling I get standing on the high board (or I don't go near it at all).
9 (r) Sailing long distances in small sailing crafts is foolhardy.	I would like to sail a long distance in a small but seaworthy sailing craft.
10 (r) Skiing down a high mountain slope is a good way to end up on crutches.	I think I would enjoy the sensation of skiing very fast down a high mountain slope.

Table D5: Regret Scale (Schwartz et al., 2002)

Statement
1 (r) Once I make a decision, I don't look back.
2 Whenever I make a choice, I'm curious about what would have happened if I had chosen differently.
3 Whenever I make a choice, I try to get information about how the other alternatives turned out.
4 If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better.
5 When I think about how I'm doing in life, I often assess opportunities I have passed up.