Payback scheme in first-price private value auctions: an experimental study

(Job Market Paper)

Ye Han

School of Economics

The University of Adelaide

ye.han@adelaide.edu.au

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Abstract

A common finding in first-price sealed bid auction is that bidders bid over the risk neutral Nash equilibrium prediction. While this behaviour is generally considered to be due to risk aversion, a growing number of papers show that an additional explanation could also play a role: loss aversion. In this paper, we design a payback scheme in first-price auctions where loss aversion can be tested directly. In this payback scheme, before the auction starts, the bidders are given a fixed amount of money to bid. Only the winner keeps the money and the losers need to pay the money back to the seller. We provide and compare the risk aversion and loss aversion equilibrium bidding models and revenue in first-price auctions in two cases: with and without the payback scheme. The model predicts that the risk neutrality and loss neutrality play the same role in bidding strategy. The scheme can increase the seller's revenue only if the bidders are loss averse. In a series of experiments, we compare the revenue and efficiency of these two designs. We find that, in terms of revenue, the payback scheme can generate more revenue only if the money given to the bidders is smaller than a critical value. However, the payback scheme has no influence on efficiency. Moreover, our design also allows us to identify the stability of risk preferences and loss aversion attitudes within bidders by comparing measures obtained from two institutions: first-price auctions and lotteries. The results suggest that elicited preferences are not stable across different institutions.

JEL classification: D44, D47, C9
Key words: First-price auction, payback scheme, Loss aversion, Risk aversion

1 Introduction

First-price sealed bid auction, as one of the four primary auction types (the other three are English, Dutch, and second-price auction) used to allocate items, is widely adopted in the field. The bidding rule is easily understood: The bidders write their bids for the item and deliver them to the auctioneer; the auctioneer determines the highest bidder, and the highest bidder gets the item for a price equal to his own bid. There are two forms of application for first-price auctions. The first is that the bidders are 'buyers', and the highest bidder wins the auction; the other is the bidders are 'suppliers' (i.e. construction contracts as in Vickrey, 1961), and the lowest bidder wins. In this paper, we focus on analysing the first-price sealed bid auction with independent private value bidders. For independent private value (IPV) auctions, each bidder knows the value of the item to himself and the distribution from which the bidders' valuations are independently drawn.

Vickrey (1961) was the first to apply game theory to build the theoretical model for independent private value actions. By assuming risk neutral bidders, he derived the unique risk neutral Nash equilibrium (RNNE) bid functions for first-price and second-price auctions given that the private values are drawn from a uniform distribution. Furthermore, he demonstrated that the first-price auction is strategically equivalent to the Dutch auction, and pointed out that the second-price auction (Vickrey auction) is equivalent to the conventional English auction.

However, overbidding in first-price auctions with independent private values is consistent with experimental findings which suggest that bidders consistently bid above the RNNE prediction (CSW, 1982; Kagel & Roth, 1995; Kagel & Levin; 2011). This overbidding anomaly was initially explained by the constant relative risk aversion model - CRRA (CSW, 1988). The intuition behind this is that the subject prefers a sure gain by submitting a higher bid to a risky but potentially greater gain with a lower bid. However, as mentioned by Kagel and Roth (1995, p. 525), 'risk aversion is one element, but far from the only element generating bidding above the RNNE', many alternative behavioural models also give explanations for this anomaly.

Goeree, Holt and Palfrey (2002) compare bidders' behaviour with a two-bidder market in two first-price private value auction treatments (low and high private values with a group of six discrete values in each). The treatments have the same RNNE bid, but differ in the curvature of the loss function. Overbidding is observed for both treatments and is more common in the high value treatment as conjectured. They find that the quantal response equilibrium (QRE) model with risk aversion fits the bidding data well, whereas the 'pure joy of winning' model is reasonable, but does significantly worse.[1]

Dorsey and Razzolini (2003) study the bidding behaviour in two equivalent environments: the first-price private value auction, and the lottery choice. In the auction experiment, each bidder competes against three simulated bidders who use the RNNE bidding strategy. With regards to the first-price auction, there are two treatments - a baseline treatment and one in which each individual is provided the probability of winning with a particular bid, after which he can either submit or revise the bid. By examining the bidding behaviour, they find that showing the subjects the probability of winning the auction causes the bids at high private values to become less aggressive and closer to the RNNE bids, thus suggesting that the misperception of the probabilities of winning plays some role in overbidding.

Filiz and Ozbay (2007) introduce regret theory, which incorporates the payoffs from the forgone alternatives in the expected utility function to explain overbidding. The study

[1] Cox, Smith, and Walker (1988) also incorporate 'Joy of winning' in their CRRA model.

implements a series of one-shot first-price auction experiments in order to analyse the impact of anticipated loser and winner regret in first-price auctions using a between-subject design. Choosing a one-shot game instead of the typical repeated rounds game rules out the learning effect. There are three treatments based on what information is revealed to all subjects at the end of the auction - that is, the winning bid (loser regret), the second highest bid (winner regret), and no information feedback. They find that subjects do not seem to anticipate winner regret, as the estimated slope of the bid function (0.77) is not significantly different from that in the no feedback treatment (0.79), whereas they do identify anticipated loser regret, as the estimated slope of the bid function is significantly higher under this condition (0.87).

So far, the explanations discussed are all based on the expected utility framework. Another strand of literature considers the endogenous reference dependence (introduced by Koszegi & Rabin, 2006) to analyse standard auctions, such as Lange and Ratan (2010). They develop the Koszegi-Rabin framework in first- and second-price auctions and find an additional explanation - loss aversion also leads to overbidding in induced private value first-price auctions.[2] For the standard first-price auction, there is no monetary loss for the bidders since the payoff for the losers is zero; they fail to buy the item but also do not pay at all. As a result, the ‘loss’ actually occurs when the bidder expects to win but loses the auction. Naturally, we consider what might happen if we come up with an auction scheme in the first-price auction in which the losers really lose some money. Would such a scheme generate even stronger overbidding? If so, we also want to know whether it will enhance the seller’s revenue, since maximising such revenue is one major goal of an auction design.

[2] However, loss aversion cannot be transferred to explain the overbidding in the field first-price private value auctions.

Therefore, we come up with a new and simple device which permits us to test the above conjectures. This device is called ‘payback’, in which each bidder receives an initial capital balance before the auction starts and can use the money when submitting his bid. However, after the highest bid has been announced, only the winner can keep the initial capital balance whereas all the losers need to ‘pay back’ the initial capital balance to the seller. Thus, within this scheme, we stimulate the losers facing a ‘loss’ relative to the situation in which they receive the initial capital balance.

Loss aversion would arguably play a role in this scheme. Kahneman and Tversky (1979) first formulated the concept of loss aversion which before was widely argued in psychology. A central result of loss aversion is that the people are much more sensitive to potential losses than potential gains. The phenomenon of loss aversion is well established in the experimental literature, and it is widely observed in both risky and riskless choice decisions (Rabin, 2000; Fehr & Goette, 2007; Kahneman, Knetsch, & Thaler, 1990).

Much of the research relevant to loss aversion also lies within neuroeconomics (Tom et al., 2007; Delgado et al., 2008). Anticipated or actual losses may cause individuals to experience negative emotions leading to loss aversion. A joint paper by cognitive neuroscientists and economists (Delgado et al., 2008) is closely relevant to this study. This novel paper provides insight into the neural circuitry of experimental auctions and uses such insight to understand overbidding. They design three treatments: baseline, ‘loss-frame’ which emphasises loss, and ‘bonus-frame’, which emphasises bonus (or gain). Overall, they find a stronger tendency to overbid in the ‘loss-frame’ treatment. Our research exploits this stronger tendency to overbid in ‘loss-frame’ auctions to potentially increase the seller’s revenue. We also provide the Nash equilibrium bidding strategies under two assumptions for bidders: risk aversion and loss aversion. This allows us to obtain a hypothesis that the seller's revenue should be increased with the payback scheme if the subjects are loss averse.

In this paper, we conduct a series of first-price private value auctions with and without the payback scheme using a within-subject design, thus eliminating the subject-specific effect. In addition, both a large market (n=6) and a small market (n=3) are chosen to compare the corresponding bidding behaviour and the revenue results.

Our study and Delgado et al. (2008) both use the same measurement for the seller's revenue: the winner's bid minus the initial capital balance given to him. However, the main experiment result is different. In Delgado et al. (2008)'s experiment, both the bids and the revenue are greater in the 'loss-frame' treatment relative to the 'baseline' treatment. To the contrary, in our payback scheme treatment, even though the subjects indeed bid higher, actually the seller's revenue is significantly less than in the standard first-price auction for the 6-bidder market and not significantly different for the 3-bidder market. Therefore, we conclude that using the payback scheme to enhance revenue depends vitally on the amount of the initial capital balance relative to the maximum possible private value. In Delgado et al. (2008), the ratio is 15%, whereas such a ratio increases to 50% in our experiment. At such a high ratio, the induced increase in bids cannot offset the cost of the initial capital balance retained by the winner, which leads to the payback scheme failing to increase revenue in our experiment.

The remainder of the paper is laid out as follows. In the next section we introduce the theoretical framework and the predictions of the Nash equilibrium bids and expected revenues. In Section 3 we present our experimental design in detail. Section 4 and 5 report the main results. In Section 6, we compare the risk aversion coefficients across different institutions, and then in Section 7 we explore the conditions when the payback scheme works in terms of enhancing revenue. More specifically, we re-estimate the bid function using the experimental data provided by Delgado et al. (2008) and compare such results with our experiment. Finally, Section 8 concludes this paper.

2 Theoretical models

2.1 Preliminaries

In this section we derive bidders' equilibrium bidding strategies in a payback scheme first-price auction. Consider there are n bidders participating in a first-price sealed-bid auction. They compete for a single object and submit sealed bids $b_1, b_2, \ldots, b_n$. The bidder who submits the highest bid is awarded the object, and pays his bid. Each bidder $i = \{1, 2, \ldots, n\}$ has a private value v_i which is an independent draw from a uniform distribution F defined on $[0, 1]$. The number of bidders n and the distribution F are common knowledge, but the value realization v_i is private information.

With the payback scheme, each bidder receives an initial capital balance K before the auction starts, and he could use any proportion of K to submit his bid. However, he keeps the money K only if he is the winner; if he loses the auction, he has to give the money K back to the seller. That is the reason why we name such a scheme 'payback'.

We derive the equilibrium bidding strategies by considering the signalling problem of bidder i, given that all other bidders $(j \neq i)$ use the same increasing, differentiable bidding strategy $b(\cdot)$ to map their own private values into bids. Bidder i is not obliged to reveal his true type v_i, so he can select a private value z_i from the uniform distribution F and submit a bid of $b(z_i)$. Next we use the revelation principle to derive the symmetric

Nash equilibrium bidding strategy. More specifically, we verify bidder i has no incentive to bid as if he had a private value $z_i \neq v_i$.

2.2 Risk Averse Symmetric Nash Equilibrium model (RASNE)

Vickrey (1961) was the first to derive the Nash equilibrium bidding function in independent private-value auctions assuming that bidders are all risk neutral. Holt (1980), Maskin and Riley (1980), and Harris and Raviv (1981) extend the Vickrey model to the case that bidders are risk averse. More specifically, they assume that the bidders display a homogeneous risk averse attitude and the corresponding expected revenue is greater than if they were risk neutral.

Since the assumption of the bidders sharing the same risk attitude is restrictive, Cox, Roberson, and Smith (1982) construct an equilibrium bidding model (CRRA) that permits bidders to differ in their risk attitudes with a utility function $u_i(y) = y^{r_i}$ where the individual constant relative risk preference parameter r_i is from a probability distribution Φ on $[0, 1]$. Each bidder knows his own risk parameter r_i as well as the probability distribution Φ. An important feature of the bid function $b_i = \frac{n-1}{n-1+r_i} v_i$ is that it only applies to bids that do not exceed $\overline{b} = \frac{n-1}{n}$ which is the maximum bid that the least risk averse (in other words, risk neutral) bidder would submit.

Cox, Smith, and Walker (1988) generalise the CRRA model to $r_i \in (0, r_{max}]$, where $r_{max} \geq 1$ which stands for the risk parameter for the least risk averse bidder. In this model, the least risk averse bidder could be a risk neutral or a risk-loving bidder, which depends on the prior belief of $r_{max.}$ We will discuss how changing r_{max} influences the estimated individual risk parameter in another paper. In this paper, we focus our analysis on the Nash equilibrium bidding strategy in a first-price payback scheme auction for homogeneous bidders.

The probability of bidder i (bidding as if he had a private value z_i) winning the auction is that all the other $n-1$ bidders' private values are smaller than z_i, which is $F(z_i)^{n-1} = {z_i}^{n-1}$. Bidder i's expected utility is defined as

$$
\begin{aligned}
E(u_i) &= {z_i}^{n-1}\big(K + v_i - b(z_i)\big)^r + (1 - {z_i}^{n-1})(K - K) \\
E(u_i) &= {z_i}^{n-1}\big(K + v_i - b(z_i)\big)^r
\end{aligned}
\tag{2.1}
$$

It must have the property that for any true private value v_i, the expected utility function (2.1) is maximised by setting $z_i = v_i$. Therefore, v_i should satisfy the below first order condition

$$
\frac{\partial E(u_i)}{\partial z_i}\Big|_{z_i = v_i} = 0 \tag{2.2}
$$

Which yields the following first order differential equation

$$
b'(v_i) = \frac{(n-1)(K + v_i - b(v_i))}{v_i r} \tag{2.3}
$$

for all v_i in the interval [0,1], equation (2.3) is solved by the following risk averse symmetric Nash equilibrium (RASNE) bidding function:[3]

$$
b(v_i)^{RASNE} = K + \frac{n-1}{n+r-1} v_i \tag{2.4}
$$

[3] The full deviation of $b(v_i)^{RASNE}$ is in Appendix B.

We substitute equation (2.4) in the second order condition $\frac{\partial^2 E(u_i)}{\partial {z_i}^2}|_{z_i=v_i} = -\frac{(n-1)}{r \cdot v_i} < 0$ which satisfies the maximising profit requirement. Therefore, if every bidder is using the same bidding function $b(\cdot)$, it is optimal for all bidders to reveal their true types.

When $r = 1$ then equation (2.4) reverts to Vickrey's benchmark risk neutral Nash equilibrium (RNNE) model

$$b(v_i)^{RNNE} = K + \frac{n-1}{n} v_i \tag{2.5}$$

2.3 Loss Averse Symmetric Nash Equilibrium model (LASNE)

In this section, instead of assuming subjects display a homogeneous risk averse attitude, we presume that they share a homogeneous loss aversion coefficient $\lambda > 0$. Such a coefficient only plays a role when subjects experience a loss. A subject with $\lambda > 1$ is loss averse, and the greater the value of λ, the more loss averse the subjects is. A subject with $\lambda = 1$ is loss neutral, whereas $\lambda < 1$ indicates the subject is gain-seeking. To simplify the model, we also assume the subjects are risk neutral where $r = 1$. Therefore, bidder i 's expected utility is defined as

$$E(u_i) = {z_i}^{n-1}\big(K + v_i - b(z_i)\big) + (1 - {z_i}^{n-1})(K - \lambda K) \tag{2.6}$$

As in the last section, for any private value v_i, the expected utility function (2.6) is maximised by setting $z_i = v_i$. Therefore v_i, should again, satisfy

$$\frac{\partial E(u_i)}{\partial z_i}|_{z_i=v_i} = 0 \tag{2.7}$$

Hence, we obtain the following first order differential equation

$$b'(v_i) = \frac{(n-1)(\lambda K + v_i - b(v_i))}{v_i} \tag{2.8}$$

for all v_i in the interval [0,1], equation (2.8) is solved by the following loss averse symmetric Nash equilibrium (LASNE) bidding function:

$$b(v_i)^{LASNE} = \lambda K + \frac{n-1}{n} v_i \tag{2.9}$$

When subjects are loss neutral (where $\lambda = 1$), then equation (2.9) also reverts to Vickrey's benchmark risk neutral Nash equilibrium (RNNE) model as in Equation (2.5).

2.4 Expected revenue predictions

In equilibrium, the seller's expected revenue is determined by evaluating the corresponding Nash equilibrium bidding strategy at the expected highest value in the uniform distribution$[0, 1]$, which is $\frac{n}{n+1}$. Hence, with regards to the RASNE model

$$ER^{RASNE} = K + \frac{n-1}{n+r-1} \times \frac{n}{n+1} - K$$

$$ER^{RASNE} = \frac{n(n-1)}{(n+r-1)(n+1)} \tag{2.10}$$

When $r = 1$ then equation (2.10) becomes

$$ER^{RNNE} = \frac{n-1}{n+1} \tag{2.11}$$

with respect to the LASNE model, the seller's expected revenue is equal to

$$ER^{LASNE} = \lambda K + \frac{n-1}{n} \times \frac{n}{n+1} - K$$

$$ER^{LASNE} = (\lambda - 1)K + \frac{n-1}{n+1} \tag{2.12}$$

When $\lambda = 1$ then equation (2.12) also becomes equation (2.11), from which we obtain that the expected revenue $ER_{k=0}^{n=6} = ER_{k=0.5}^{n=6} = 0.71$and $ER_{k=0}^{n=3} = ER_{k=0.5}^{n=3} = 0.50$.

In addition, the predictions allow us to formulate the following hypotheses:

Hypothesis 1a (RASNE): $R_{k=0}$ = $R_{k=0.5}$

Hypothesis 1b (LASNE): $R_{k=0.5} \geq R_{k=0}$ $(if\ \lambda \geq 1)$

Hypothesis 2: (RASNE & LASNE): $R_{n=6}$ > $R_{n=3}$

3 Experimental design

We ran the experiments using the software Z-Tree at the University of Adelaide's 'Adelaide Laboratory for Experimental Economics' (Adlab) in April of 2016. Sixty subjects from the undergraduate and postgraduate population of the University were recruited by the ORSEE system and participated in 4 sessions. In a given session, each subject participated in 4 experiment stages: two lottery experiments and two auction experiments. Quiz questions were given to subjects before each experiment stage, and a stage only began when all subjects answered the quiz questions correctly. Each session lasted about 90 minutes. Subjects received written instructions which were read aloud and could ask questions to the experimenter in private. A copy of the experimental instructions is given in Appendix A. Including a show-up fee of $10, subjects earned $20 on average.

The result of each experiment was not revealed until the end of the session, in order to keep the decision for each experiment task independent. The subject was paid according to his aggregate payoffs from the 4 experiment stages.

3.1 The first lottery experiment stage

The aim of the first lottery experiment is to measure subjects' loss aversion attitudes. Subjects decided whether or not to accept 14 risky lotteries as shown in the first column of Table 3.1, one of which would be randomly selected for payment. For each lottery, there is a 50% chance of winning and a 50% chance of losing.

To determine which lottery would be chosen, a number between 1 and 14 was randomly drawn for each subject. If the subject chose to 'Accept' the corresponding lottery, his final payoff was adjusted according to the result of the lottery; if the subject chose to 'Reject', then he got zero from this experiment task. As explained earlier, in order to keep the decision for each experiment task independent, the result of this first lottery experiment was not revealed to the subject until the end of the session.

Table 3.1 **The design of the 14 risky lotteries in the first lottery stage**

Lottery 50%/50% chance	Expected Value
#1 Lose $0.5 or win $9.5	$4.50
#2 Lose $1 or win $9	$4
#3 Lose $1.5 or win $8.5	$3.50
#4 Lose $2 or win $8	$3
#5 Lose $2.5 or win $7.5	$2.50
#6 Lose $3 or win $7	$2
#7 Lose $3.5 or win $6.5	$1.50
#8 Lose $4 or win $6	$1
#9 Lose $4.5 or win $5.5	$0.50
#10 Lose $5 or win $5	$0
#11 Lose $5.5 or win $4.5	-$0.5
#12 Lose $6 or win $4	-$1
#13 Lose $6.5 or win $3.5	-$1.5
#14 Lose $7 or win $3	-$2

3.2 The second lottery experiment stage

Following the completion of the first lottery task, a second lottery experiment was conducted for eliciting subjects' certainty equivalents for 11 lotteries.[4] Each lottery, initially owned by the subject, has a 50% chance of a high payoff H and a 50% chance of a low payoff L as shown in columns 1-3 of Table 3.2. Certainty equivalents were elicited using the Becker-DeGroot-Marschak (BDM) (1963) incentive mechanism, which gives the subject an incentive to report his true valuations for the corresponding lotteries. The procedure was as follows. The subject was asked to state a minimum selling price p_s (between the high and low payoff) for each lottery, with the knowledge that a random buying price p_b (also between the high and low payoff) would be drawn to determine if the lottery would be sold to the computer. If $p_b \geq p_s$, the subject received the randomly drawn buying price; otherwise, he received the outcome of the lottery.

As with the first lottery experiment, only one lottery would be chosen for each subject to decide his payoff in this BDM lottery task, and the result would not be revealed until the end of the session.

[4] We used the same 11 lotteries as in Kocher, Pahlke, and Trautmann (2010). The differences between the high and low payoffs for the lotteries are always even numbers: 2, 4, 6, 8, and 10. It makes the arithmetic easier for subjects.

Table 3.2 The design of the 11 lotteries in the second lottery stage

Lottery	High payoff (50% chance)	Low payoff (50% chance)	Expected value
#1	12.76	4.76	8.76
#2	8.30	2.30	5.30
#3	10.70	2.70	6.70
#4	6.52	2.52	4.52
#5	13.22	5.22	9.22
#6	8.06	2.06	5.06
#7	6.36	2.36	4.36
#8	13.20	3.20	8.20
#9	9.76	5.76	7.76
#10	12.76	6.76	9.76
#11	8.01	2.01	5.01

Note: Numbers in columns 2-4 show amounts in AUD. The expected value for the corresponding lottery was not shown to the subjects.

3.3 The auction experiment stages

The auction experiment was designed to test whether the payback scheme enhances the seller's revenue. We used within-subject variation. Therefore, subjects were exposed to two treatments: standard first-price auction, and payback scheme first-price auction, which we refer to as k0 and k5 treatment hereafter. In both auction stages, subjects were in the same group of six bidders for 20 rounds. The k0 treatment is the control treatment since it accords with a large number of laboratory studies.

In this paper, the k5 treatment is the novel treatment. In the k5 treatment, subjects received $5 as the initial capital balance they could use to bid before each auction started. Only the winner got to keep the $5; all the losers had to pay the $5 back. Due to the order effect that exists in the within-subject design, it was necessary to run the treatments in both orders: k0k5 order and the reverse, k5k0 order. In the k0k5 order of the treatment, subjects participated in the standard private value first-price auction for the first 20 rounds and then for the second 20 rounds, they were switched to the conditions of the payback scheme. With respect to the k5k0 order, subjects were exposed to the treatments in reversed order.

To study the effect of the payback scheme on seller's revenue, we also examined two different market sizes: 6-bidder market and a 3-bidder market using a between-subject design. For both market sizes, at the beginning of the auction stage, the computer randomly allocated subjects to markets of size $n = 6$. Additionally, to form the 3-bidder market, in each auction round, the fixed group of six bidders was re-matched into two 3-bidder markets.[5] This matching method, on the one hand, provides independent units of observation. On the other hand, it constitutes a comparison with the 6-bidder market. We use the notation k0k5_6 to represent the experiment session with the k0k5 order in a 6-bidder market.

In each round, subjects' private values were independently drawn from a uniform distribution defined on [$0, $10]. Each subject was required to submit a bid equal to or below his private value in the k0 treatment, and equal to or below his private value plus $5 in the k5 treatment. The winner was the subject who submitted the highest bid and paid a price equal to his bid. In the case of a tie, the winner was randomly chosen among the bidders who submitted the highest bid. In each market, at the end of each auction round, the winner's bid (but not identity) was disclosed to all the subjects. Table 3.3 summarises our auction experiments.

[5] Such a design is similar to Schram and Onderstal (2009), except that in their experiment, the subjects did not know the 3-bidder market was formed within the fixed group of six bidders.

Each subject's payoff in the two auction stages was decided by the computer, which randomly chose two auction rounds for each treatment. The summation of the payoffs from the four rounds was the subject's payoff from the auction experiment.

Table 3.3 The design of the auction experiments

Market size	Session	Treatment	# Subjects	# Groups
6	k0k5_6	$K0_1, K5_2$	18	3
	k5k0_6	$K5_1, K0_2$	18	3
3	k0k5_3	$K0_1, K5_2$	12	2
	k5k0_3	$K5_1, K0_2$	12	2

4 Descriptive analysis for two lottery tasks

4.1 Loss aversion

As in Rabin (2000) and Fehr and Goette (2007), the rejection of a small-stake risky lottery with a positive expected value can be interpreted as loss aversion instead of risk aversion. So we can use the first lottery task to measure the subject's loss aversion attitude. In this task, the least loss-averse (i.e. the most gain-seeking)[6] subject would choose to accept all 14 lotteries because of the 50% chance of winning some money, even though the expected values are negative from lottery #11 to lottery #14. To the contrary, an extremely loss-averse subject would choose to reject all the 14 lotteries since all the lotteries include a 50% chance of losing money. Overall, a subject would reject more lotteries if he is more loss-averse. Hence, we can use a subject's switch point from accepting to rejecting a specific lottery to measure his loss aversion. Among all the 60 subjects, four subjects have

[6] Here, we adopt the terminology 'gain-seeking' as per Abdellaoui, Bleichrodt and L'Haridon (2008).

more than one switch point (6.67% of all the subjects). For these subjects, we only analyse the first switch point as per Prasad and Salmon (2013).[7]

Before devising a framework to calculate each subject's loss aversion coefficient, it is necessary to first have a general idea about the distribution of accepted lotteries among all the 60 subjects. Figure 4.1 shows the distribution of the number of accepted lotteries in the loss aversion measurement stage. The mode of the number of accepted lotteries is 6 (12 subjects), in which the expected value is $2.

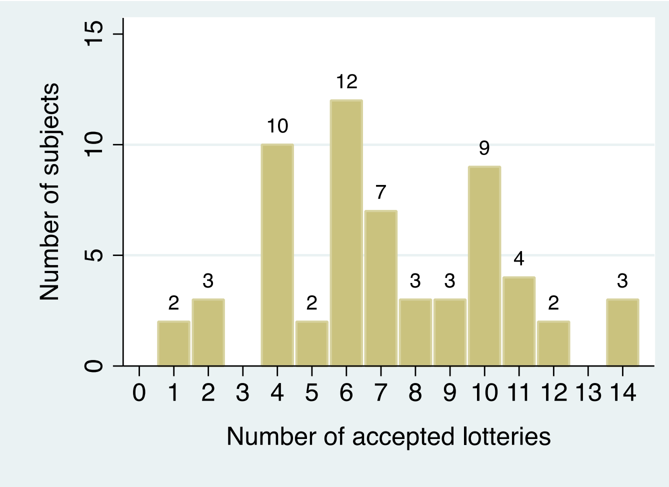

Figure 4.1 Distribution of the number of accepted lotteries

Suppose the lottery chosen to determine the subject's payoff is (50% chance of winning w, 50% chance of losing w'). We adopt the expected utility framework to illustrate the utility a subject gets from the first lottery stage:

$$u(w) = \begin{cases} w, & w \geq 0 \\ \lambda w', & w' < 0 \end{cases}$$

[7] Some papers, like Laury and Holt (2005), only investigate the 'one switch point' choice pattern and ignore those subjects with more than one switch point.

where λ is the loss aversion coefficient. The first equation represents the utility of a subject winning whereas the second equation measures the disutility of losing. A larger loss aversion coefficient λ represents that the subject is more loss-averse, as the feeling of losing money is more painful. A subject will accept a lottery if:

$$prob(gain)u(w) + prob(lose)u(w') > 0$$

A subject will reject a lottery if:

$$prob(gain)u(w) + prob(lose)u(w') < 0$$

When a subject is indifferent between accepting and rejecting a lottery, it must be that:

$$prob(gain)u(w) + prob(lose)u(w') = 0$$
$$prob(gain) = prob(lose) = 50\%$$
$$u(w) + u(w') = 0$$
$$w + \lambda w' = 0$$
$$\lambda = -\frac{w}{w'}$$

The above equation is satisfied when we exactly know the lottery for which the subject is indifferent between accepting and rejecting. However, we can only observe a switch point for each subject. For instance, if a subject accepts the first 2 lotteries, but rejects the next 12 lotteries, we know the accurate indifferent lottery must lie between #2 and #3. Therefore, according to this model, the loss aversion coefficient λ must lie in the interval (5.67, 9]. As mentioned by Anderson and Mellor (2009), a common technique for dealing with this estimation problem is to use an interval regression model. The below model accounts for interval censoring of the dependent variable, in this scenario loss aversion coefficient λ, as well as left and right censoring.[8] The subjects who accept between 1 and 13 lotteries are interval censored observations; those who accept all the 14 lotteries are left censored observations;[9] as for the subjects who reject all the lotteries, they are right censored observations.

$$\lambda_i^* = \mu + \varepsilon_i \tag{4.1}$$

We do not observe subject i's loss-averse attitude λ_i ($\lambda_i > 0$) directly. However, we instead observe y_i, which indicates the number of lotteries that subject i accepts. The notation y_i implies a range for λ_i^*, which is delimited by $[\lambda_{min}, \lambda_{max}]$. For this reason, instead of λ_i, we model the latent variable λ_i^* as in equation (4.1). In equation (4.1), ε_i is a normally distributed error with mean zero and variance σ^2.

A maximum likelihood procedure has been used to estimate this model. After obtaining the estimated intercept μ, subject i's expected loss aversion coefficient given the corresponding number of accepted lotteries is computed in the following way:

---

[8] Interval censoring describes the case when a data point is somewhere on an interval between two values. Left (right) censoring represents that when a data point is below (above) a certain value but it is unknown by how much.

[9] However, we know that the loss aversion coefficient must be a positive figure. So for those who accept all the 14 lotteries are still interval censored observations.

$$E[\lambda_i^* \mid y_i = 0] = E(\lambda^*) \frac{\Phi(-\sigma + b)}{\Phi(b)}$$

$$E[\lambda_i^* \mid y_i \in \{1,...,13\}] = E(\lambda^*) \frac{\Phi(\sigma - a) - \Phi(\sigma - b)}{\Phi(b) - \Phi(a)}$$

$$E[\lambda_i^* \mid y_i = 14] = E(\lambda^*) \frac{\Phi(\sigma - a)}{\Phi(-a)}$$

$$E(\lambda^*) = \exp(\mu + \frac{\sigma^2}{2})$$

$$a = \frac{\lambda_{\min} - \mu}{\sigma}$$

$$b = \frac{\lambda_{\max} - \mu}{\sigma}$$

The range of $[\lambda_{min}, \lambda_{max}]$ for the corresponding number of accepted lotteries and the expected loss aversion coefficient λ^* are shown in Table 4.1. We also report the related percentage of subjects for each number of accepted lotteries. Within all the 60 subjects, 15% of them accept all ten lotteries with a non-negative expected value, a further 15% of subjects accept at least one lottery with a negative expected value, and the remaining 70% of subjects reject at least lottery #10 (which has an expected value of zero) or some lotteries even with positive expected values. The median subject accepts lotteries #1 to #7, which implies that the median value of λ is 1.68.[10] Such a result is qualitatively similar to the median value of λ (2.25) reported by Tversky and Kahneman (1992). Hence, we find that loss aversion is a significant pattern for the subjects.

It is instructive to compare the results with those of a similar experiment. The paper by Gächter, Johnson, and Herrmann (2007) measure the individual-level loss aversion using six 50-50 lotteries. The winning money is fixed at €6, whereas the loss varies from €2 to

[10] We can think of an example to have a intuitively understanding of $\lambda = 1.68$. That is, a subject must gain $1.68 to offset the disutility of losing $1. Therefore, as λ increases, a subject need to gain more money to compensate the disutility of losing $1. The subject is more loss averse, so to speak.

€7. They find a similar result that the median subject has a loss aversion coefficient $\lambda = 1.2$.

Table 4.1 The loss aversion parameter for the corresponding number of accepted lotteries

# Accepted Lotteries	# Subjects	Percentage (%)	Cum. Percentage (%)	$[\lambda_{min}, \lambda_{max}]$	λ
0	0	0.00	0.00	(19, ∞)	n.a.
1	2	3.33	3.33	(9, 19]	9.49
2	3	5.00	8.33	(5.67, 9]	6.44
3	0	0.00	8.33	(4, 5.67]	n.a.
4	10	16.67	25.00	(3, 4]	3.47
5	2	3.33	28.33	(2.33, 3]	2.66
6	12	20.00	48.33	(1.86, 2.33]	2.10
7	7	11.67	60.00	(1.5, 1.86]	1.68
8	3	5.00	65.00	(1.22, 1.5]	1.36
9	3	5.00	70.00	(1, 1.22]	1.11
10	9	15.00	85.00	(0.82, 1]	0.91
11	4	6.67	91.67	(0.67, 0.82]	0.75
12	2	3.33	95.00	(0.54, 0.67]	0.61
13	0	0.00	95.00	(0.43, 0.54]	n.a.
14	3	5.00	100.00	(0, 0.43]	0.22

Note: 'Cum. Percentage' represents the cumulative percentage. Where the value for λ is 'n. a.', no subject accepts the corresponding number of lotteries.

4.2 Risk aversion

Becker, DeGroot, and Marschak (1964, BDM) originally devised a method to determine a monetary equivalent of a wager. Harrison (1986) subsequently applied this method to elicit a subject's risk aversion attitude. The basic idea of the BDM method is to endow the subject with a series of predetermined lotteries and ask him for a selling price for each lottery with the acknowledgment that a buying price is generated randomly irrespective of the selling price he asks. By this method the subject has an incentive to truthfully reveal the certainty equivalent (CE) of a given lottery.

Before computing each subject's risk aversion coefficient, it is useful to statistically compare the CE and the expected value for the 11 lotteries. We report the corresponding figures as well as the results from Kocher, Pahlke, and Trautmann's (KPT) (2010) experiment in Table 4.2. Four out of 11 lotteries' average CEs are greater than the corresponding expected values. With regards to KPT's experiment, all the 11 lotteries' CEs are smaller than the corresponding expected values.

Table 4.2 The average certainty equivalent for each lottery in our experiment and KPT's experiment

Lottery	Expected Value	Average CE	Average CE (KPT)
#1	8.76	**8.80**	7.82
#2	5.30	4.99	5.00
#3	6.70	**6.82**	6.03
#4	4.52	4.29	4.10
#5	9.22	**9.59**	8.54
#6	5.06	4.83	4.70
#7	4.36	4.05	3.94
#8	8.20	**9.08**	7.83
#9	7.76	7.53	7.22
#10	9.76	9.66	8.93
#11	5.01	4.76	4.68

Note: 'Average CE' is the average certainty equivalent in our experiment; 'Average CE (KPT)' stands for the average certainty equivalent in KPT (2010). Figures in bold font are greater than the corresponding expected values.

Next, it is necessary to identify the extent of each subject's risk aversion coefficient within the expected utility framework. We denote the utility function when a subject receives money w:

$$u(w) = w^r, r > 0$$

In such a utility function, the notation r is the risk preference parameter whereas $(1 - r)$ is the Arrow-Pratt measure of the relative risk aversion coefficient.[11] If a subject states a selling price p_s for a lottery with a 50% chance of getting a high payoff H and a 50% chance of getting a low payoff L, then it must be that the utility of the monetary payoff p_s is the same as the utility from the risky lottery, such that:

$$u(p_s) = prob(H)u(H) + prob(L)u(L)$$
$${p_s}^r = 0.5H^r + 0.5L^r$$

As per KPT (2010, p. 13) we also use a nonlinear least squares technique to estimate each subject's risk preference coefficient r based on the selling price p_s that he states, as well as the given lottery's high payoff H and the low payoff L. The model we use is as follows:

$$p_{s_i} = (0.5H^{r_i} + 0.5L^{r_i})^{\frac{1}{r_i}} + u_i \qquad (4.2)$$

in equation (4.2), the normal distribution error term u_i has a property of mean zero and variance σ^2

[11] Relative risk aversion coefficient is calculated as follows: $(w) = -w \cdot \frac{u''(w)}{u'(w)}$.

Table 4.3 Risk preference classification and the corresponding number of subjects

Range of risk preference	# Subjects (Percentage)	Total	KPT: # Subjects (Percentage)	Total	Risk preference classification
(1.95, ∞)	15 (25%)	27 (45%)	3 (2%)	27 (18%)	highly risk loving
(1.49, 1.95]	5 (8.33%)		6 (4%)		very risk loving
(1.15, 1.49]	7 (11.67%)		18 (12%)		risk loving
(0.85, 1.15]	11 (18.33%)	11 (18.33 %)	34 (22.67%)	34 (22.67 %)	risk neutral
(0.59, 0.85]	6 (10%)	22 (36.66 %)	23 (15.33%)	89 (59.33 %)	slightly risk averse
(0.32, 0.59]	3 (5%)		17 (11.33%)		risk averse
(0.03, 0.32]	2 (3.33%)		18 (12%)		very risk averse
(-0.37, 0.03]	3 (3.33%)		15 (10%)		highly risk averse
(-∞, 0.37)	9 (15%)		16 (10.67%)		stay in bed

Note: We obtained KPT's experiment data from Appendix D. of ScienceDirect website http://www.sciencedirect.com/science/article/pii/S0014292115000677.

In Table 4.3, we report the estimated range of the risk preference coefficient r and the corresponding number of subjects in our experiment as well as in KPT's experiment.[12] Here, we follow the risk preference classification as per Holt and Laury (2002). In our experiment of 60 subjects, 45% of them are risk loving; whereas 11 subjects (18.33%) are risk neutral, and the remaining 22 subjects (36.66%) are risk averse.

The results from KPT's experiment are inconsistent with our finding. That is, the majority of subjects are risk averse (59.33%) and only 18% of subjects are risk loving while 22.67% of subjects are risk neutral.[13,14]

[12] KPT does not report subjects' risk aversion preferences in both the 2010 and 2015 papers. However, we can obtain such results using the data and the code they provide in the 2015 paper.
[13] We have excluded the possibility that the difference is due to the 11 lotteries being presented to the subjects in a different manner between our experiment and KPT's. For both experiments, the 11 lotteries are shown to the subjects on 11 separate pages.
[14] However, these results are close to the findings reported by Berg, Dickhaut and McCabe (2003). In their design, the basic essence of the BDM method is the same. But instead of a 50-50 lottery, they use a 30-sided die and a cut-off value p to decide the payoff for the subject if his selling price is above the randomly generated buying price. Hence, they find that within 48 subjects, about 55% of them are risk loving.

After identifying each subject's loss aversion coefficient λ and risk aversion coefficient $(1-r)$, we wonder whether these two coefficients are related to each other as Thaler et al. (1997) suggest. In their experiment, the subjects need to make some investment decisions between two funds – bond and stock funds, within four conditions – monthly, yearly, five-yearly, and inflated monthly. A major conclusion they get is: "Investors who display myopic loss aversion will be more willing to accept risks if they evaluate their investments less often." In this BDM lottery experiment, if we consider a lottery decision as an investment, the subject can only know the result of the investment at the very end of the experiment. This prohibits them from adopting a 'narrow framing' as defined by Kahneman and Lovallo (1993) – in other words, considering decision problems one at a time. As a result, it is not very surprising that 45% of subjects are risk loving.

In order to examine whether the two estimation parameters are correlated, we create a scatter plot of the $(1-r)$ and λ along with histograms of the two variables as in Figure 4.2.[15] We can see that there is no clear linear correlation between these two variables.[16] In terms of the risk aversion coefficient, most subjects cluster in the range of [-2, 2]. With regards to the loss aversion coefficient, the majority of subjects are between 0 and 4.[17]

Our result is very different from the result reported by Goldstein, Johnson, and Sharpe (2008), in which they find that for the 570 subjects in their experiment, the estimates of the risk aversion and loss aversion parameters are correlated.[18] Most of their subjects displayed a low risk aversion, as well as a low loss aversion attitude. It is acknowledged

[15] In figure 4.2, we have eliminated two outliers with an extremely large negative risk aversion coefficient (-273.6), which shows that the corresponding subjects are extremely risk loving. In the BDM lottery stage, the two subjects both stated a selling price H for all the 11 lotteries.
[16] We also cannot observe a linear relationship when we use $(\sum p_s, accepted\ lotteries)$ as variables to plot the chart.
[17] As a robustness check, the nonparametric Spearman test shows that for the 58 $(1-r,\lambda)$ pairs, the two variables are independent from each other (p-value > 0.1).
[18] The two variables have a very clear linear correlation not only from the chart but also verified by a Pearson correlation test.

that besides the distinction of the two experimental designs, the inconsistency of the results could be due to sample size differences.

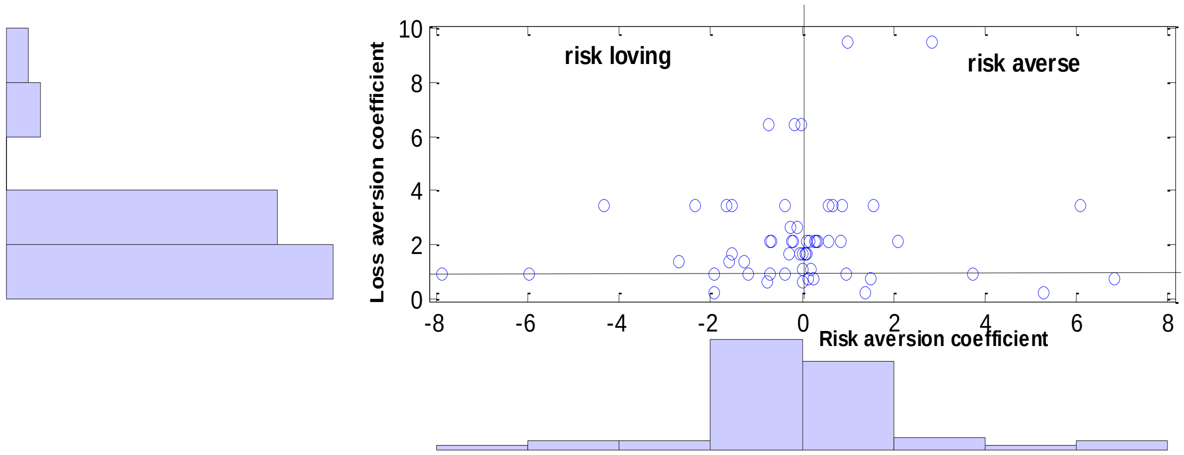

Figure 4.2 Graphical illustration of the relationship between loss aversion and risk aversion coefficients using a scatter plot and histograms.

5 Experimental results for auction stages

5.1 Modelling bid behaviour

In order to identify how the payback scheme works in the first-price auctions, in this section we use a panel data regression approach to estimate the aggregate bid functions.

As mentioned before, we use a within-subject design for the auction experiment, in which each subject experiences two first-price auction treatments: standard (k0) and a novel payback scheme (k5). Neugebauer and Perote (2008) also use a within-subject design to compare the bids of first-price auctions in two treatments: with and without the information feedback. In this paper we follow their method to model the bidding behaviour. The model is as follows

$$bid_{kit} = \beta_0 + \beta_1 Dk_{kit} + \beta_2 pv_{kit} + \beta_3 Dk_{kit} pv_{kit} + v_k + \varepsilon_{kit} \tag{5.1}$$

In equation (5.1), bid_{kit} and pv_{kit} denote the bid and the private value of subject i of group k in round t, where $i = \{1, 2, ..., 6\}, k = \begin{Bmatrix} 1,2,3 & n=6 \\ 1,2 & n=3 \end{Bmatrix}, t = \{1, 2, ..., 40\}$. β_j are the parameters to be estimated, $j = \{0, 1, 2, 3\}$, ε_{kit} is an error term, which is assumed to have mean zero and varianceσ_ε^2; v_k is the group-specific term. This model accounts for the possible structural changes between the k0 and k5 treatments by using a dummy variable Dk_{kit}, which takes the value one for the k5 treatment and zero for the k0 treatment. Since this dummy variable interacts with both the intercept and the slope, we can interpret the results from Table 5.1 as the bid functions for each treatment.

As in Section 1.2, we derive the RNNE and LASNE bidding strategies in the case of first-price private value auctions with a payback scheme as follows

$$b(v_i)^{RNNE} = K + \frac{n-1}{n} v_i$$

$$b(v_i)^{LASNE} = \lambda K + \frac{n-1}{n} v_i$$

As illustrated in Section 4.1, the subjects are loss averse on average ($\lambda > 1$). Therefore, if the subjects bid according to the RNNE or LASNE model, we have the following hypotheses

$$H1_0: \beta_1 \geq 5$$

$$H2_0: \beta_3 = 0$$

The null hypothesis is that the payback scheme should only influence the intercepts while not affecting the slopes. We start by discussing the estimated intercepts. From the coefficients of the dummy variable Dk_{kit} shown in Table 5.1 below, we can find that

$\beta_1 < 5$ which implies that the subjects would not use all of the $5 given to them to submit their bids in the payback auctions. In three of the four sessions, on average, subjects use around $4 (80% of $5) to bid. For the $k5_1$ treatment in the 3-bidder market, the subjects on average only use around $3 (60% of $5) to bid. This result suggests that the RNNE and LASNE models both fail to explain the realized bids for the payback first-price auctions, as they overestimate the impact of the payback scheme on the intercept.

Table 5.1 also reveals that β_3 is significantly positive in the last session: k5k0_3. Bids in the payback scheme treatment involve a significantly higher fraction (0.153) of private value than the standard first-price treatment, which is inconsistent with the RNNE and LASNE predictions.

Result (payback scheme effect): in all four sessions of the payback first-price auctions, the subjects use some but not all of the initial capital balance k to submit bids. Furthermore, the subjects reveal a higher fraction of their private values in the session with a 3-bidder market where subjects are exposed to the payback scheme before experiencing the standard auction.

Table 5.1 Coefficients of random effect regression: linear bid function

Independent Variable	n=6 k0k5	n=6 k5k0	n=3 k0k5	n=3 k5k0
	Dependent variable: bid			
Intercept	-0.391	-0.313	-0.079	0.002
	(0.277)	(0.185)	(0.209)	(0.001)
Dk	4.065*	4.067*	4.097*	2.914*
	(0.306)	(0.535)	(0.304)	(0.172)
pv	0.878*	0.948*	0.702*	0.790*
	(0.030)	(0.014)	(0.048)	(0.032)
Dk X pv	0.050	0.016	0.093	0.153*
	(0.099)	(0.062)	(0.059)	(0.742)
R^2 overall	0.762	0.840	0.887	0.736
# Observations	720	720	480	480
# Groups	3	3	2	2

*Note: estimate for equation 5.1, (robust standard error in parentheses); * significant at 5%.*

After identifying the treatment effect of the novel payback scheme, it is also instructive to analyse the bidding behaviour in the control treatment: standard first-price auctions. If the subjects bid according to the RNNE model, we have the following hypotheses

$$H3_0: \beta_0 = 0$$
$$H4_0: \beta_2 = 0.83\ (n = 6)$$
$$\beta_2 = 0.67\ (n = 3)$$

From Table 5.1, we can verify that $H3_0$ is correct. At the same time, subjects' bids as a fraction of private value are substantially greater in the $k0_2$ treatment compared with the $k0_1$ treatment for both the 3-bidder and 6-bidder markets. It may be that subjects get used to submitting high bids during the payback scheme and as a result continue to submit high bids once the payback scheme is removed ('anchoring').[19] Therefore, we observe an order effect in bidding behaviour for the k0 treatment.

Result (order effect in the k0 treatment): for the standard first-price auctions, the subjects bid a higher fraction of their private values if they experience the payback scheme first.

When we take a closer look at β_2 in four sessions, we cannot reject $H4_0$ for the two $k0_1$ sessions. However, we have to reject $H4_0$ in favour of the alternative hypothesis that β_2 is greater than the corresponding RNNE prediction for the two $k0_2$ sessions. Overall, in the standard first-price auctions where the subjects have no experience of the payback scheme, the bidding behaviour can be explained by the RNNE prediction; for the subjects who have experienced the payback scheme in advance, their bids exceed the RNNE prediction.

Result (bid vs RNNE prediction in the k0 treatments)*:*

$$\text{For the } k0_1 \text{ treatment: } bid_{n=6} = bid_{n=6}^{RNNE}; bid_{n=3} = bid_{n=3}^{RNNE}$$
$$\text{For the } k0_2 \text{ treatment:} bid_{n=6} > bid_{n=6}^{RNNE}; bid_{n=3} > bid_{n=3}^{RNNE}$$

We also use Figure 5.1 to demonstrate the relationships between the realized bids and the corresponding RNNE predictions for two markets in standard auctions while considering the order effect. Such plots clearly show an overbidding pattern for the $k0_2$ treatment.

[19] We do not find any evidence that learning (experiment rounds) plays a role in bidding behaviour, which may be because in our experiment, each treatment only lasts for 20 rounds.

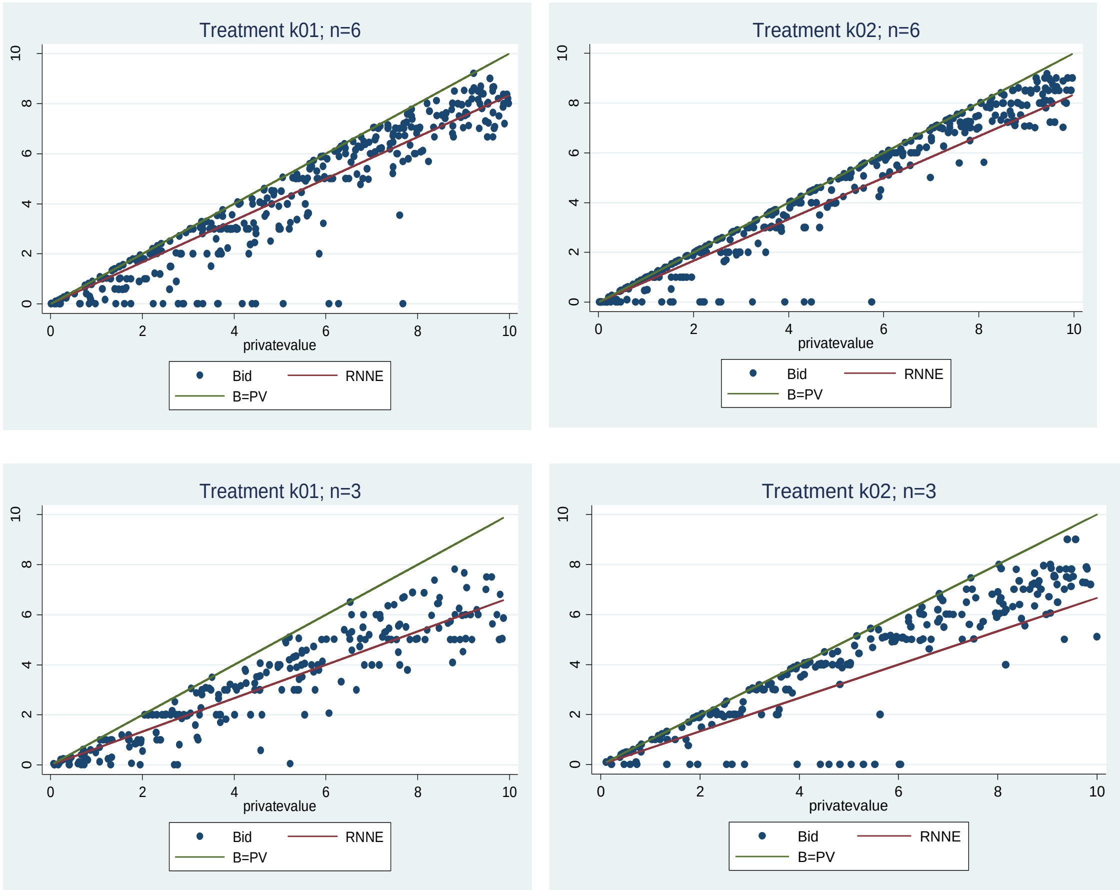

Figure 5.1 The bids and the RNNE predictions in the k0 treatment

5.2 Seller's revenue and the allocation efficiency

Revenue and efficiency are the two main measurements for evaluating an auction format. Since in this paper, the major research question is whether or not applying a payback scheme can enhance the seller's revenue, we first analyse the realized revenue by checking the two hypotheses in Section 2.4.

Before using econometric methods to verify the conjectures, we first report the revenue statistics in Table 5.2.[20] From Table 5.2, we can observe that the $k0_2$ treatment brings the greatest revenue for both market sizes on average (7.93 and 6.32, respectively). Besides

[20] With the payback scheme, since we need to take the $5 given to the winner into consideration, the realized revenue=winner's bid-$5.

this, between the two market sizes, the revenue in the 6-bidder market is always greater. Such findings are consistent with our results for the estimated bidding functions as illustrated in the previous section.

Table 5.2 The statistics of average revenue and efficiency of the two treatments for both market sizes

				Revenue		Efficiency	
	Treatment	Batch	# Observations	Mean	S.D.	Mean	S.D.
n=6	k0	1	60	7.39	1.02	98.21%	0.05
		2	60	7.93	0.96	98.56%	0.04
	k5	1	60	7.5	1.43	97.48%	0.06
		2	60	7.06	1.14	93.59%	0.16
n=3	k0	1	40	5.11	0.97	96.92%	0.08
		2	40	6.32	1.10	95.14%	0.14
	k5	1	40	5.4	1.64	88.91%	0.19
		2	40	5.12	1.20	93.42%	0.12

Note: With respect to the third column 'Batch': '1' and '2' represent the corresponding treatment in auction rounds 1-20 and 21-40, respectively. 'Mean' is obtained by taking the average of each group across 20 rounds with the specific treatment and batch. 'S.D.' is the standard deviation of the average.

In this section, we use a random effect panel data regression model similar to that used by Schram and Onderstal (2009), which includes variables for both treatment effect and order effect. In this paper, the model explaining realized revenue is given by:

$$R_{kt} = \beta_0 + \beta_1 Dk_{kt} + \beta_2 Order_{kt} + u_k + \varepsilon_{kt} \tag{5.2}$$

where dummy variable $Order_{kt} = \begin{cases} 0, & k0k5 \\ 1, & k5k0 \end{cases}$. The other variables are the same as in equation (5.1). Therefore, the control treatment is the standard first-price auction with no experience about the payback scheme ($k0_1$). Table 5.3 shows the results. The estimated coefficient of Dk_{kt} is significantly negative in the 6-bidder market (-0.38) whereas it is insignificant in the 3-bidder market.

Revenue Result (payback scheme effect): $R_{k5}^{n=6} < R_{k0}^{n=6}; R_{k5}^{n=3} = R_{k0}^{n=3}$

At the same time, we can see that the coefficient of $Order_{kt}$ is significantly positive for both market sizes, indicating that the revenue for the standard first-price auction is greater when the subjects have experienced the payback scheme. This result is consistent with our finding in the previous section that the estimated slope is greater in the $k0_2$ treatment compared to the $k0_1$ treatment. Furthermore, this coefficient is larger in the 3-bidder market. Figure 5.2 plots the difference between the realized price and the RNNE predicted price for each round in both the 3- and 6-bidder markets in the corresponding $k0_1$ and $k0_2$ treatments. We can see that for the $k0_2$ treatment, the differences between the realized prices and the RNNE predicted prices are invariably above zero, especially for the 3-bidder market, and such differences are much greater than in the $k0_1$ treatment.

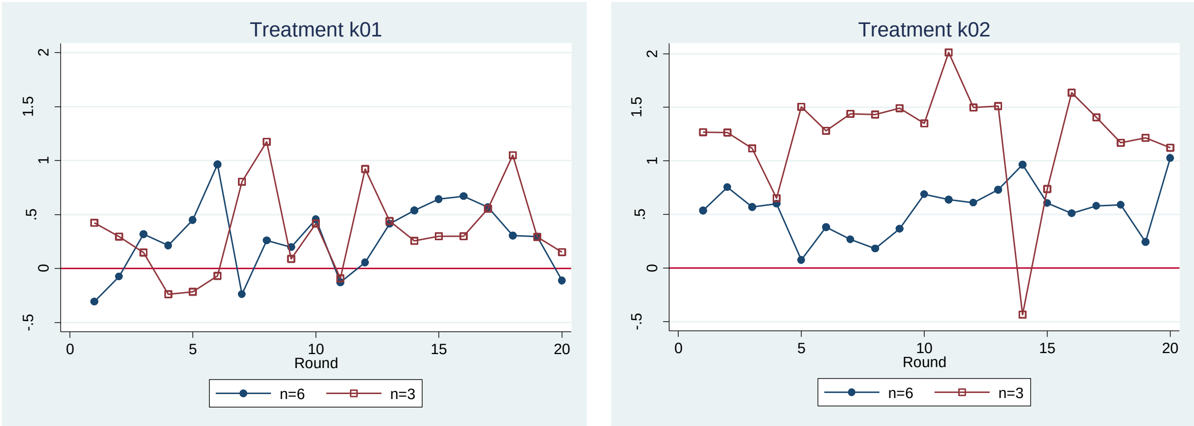

Figure 5.2 The difference between observed prices and RNNE prices in the $k0_1$ and $k0_2$ treatments

Note: In the 6-bidder market, for each auction round in a given treatment we compute the average difference between the realized prices and the RNNE-predicted prices across the associated 3 groups. In the 3-bidder market, we follow the same method, except that there are only 2 groups in a given treatment.

Revenue Result (order effect): $R_{k0_2} > R_{k0_1}$
$(R_{k0_2} - R_{k0_1})_{n=3} > (R_{k0_2} - R_{k0_1})_{n=6}$

There are two earlier papers which also compare the realized prices with the RNNE prediction in first-price auctions of 3-bidder and 6-bidder markets. Cox, Roberson, and Smith (1982) find that the RNNE prediction cannot be rejected for the 3-bidder market whereas in the 6-bidder market, overbidding behaviour is observed. However, Dyer, Kagel, and Levin (DKL) (1989) identify a different result, which is that the winning bids exceed the RNNE prediction for both 3- and 6-bidder markets.[21]

Besides revenue differences due to the treatment effect and the order effect, ***Hypothesis 2:*** $R_{n=6} > R_{n=3}$ is easily verified as the coefficient of the intercept term is significantly greater in the 6-bidder market.

Revenue Result (6-bidder market vs 3-bidder market): $R_{n=6} > R_{n=3}$

[21] DKL (1989) use a within-subject design that each subject submits two contingent bids for 3- and 6-bidder markets.

Table 5.3 Coefficients of random effect and pooled Ordinary Least Squares (OLS) regressions for two market sizes

Independent Variable	Dependent variable: Revenue n=6 RE model	n=6 Pooled OLS	n=3 RE model
Intercept	7.41*	7.41*	5.35*
	(0.138)	(0.136)	(0.159)
Dk	-0.37*	-0.38*	-0.50
	(0.075)	(0.078)	(0.330)
Order	0.49*	0.49*	0.77*
	(0.153)	(0.150)	(0.104)
#Observations	240	240	160
BP test	p=0.32		p<0.05

*Note: estimate for equation (5.2), (robust standard error in parentheses); * significant at 5%. For each revenue observation with 3-bidder market of each group k, in each round t, we compute the average revenue for two subgroups. The BP test (Breusch and Pagan test) for random effect tests* $var(u_k) = 0$*, is rejected for the 3-bidder market, but not for the 6-bidder market.*[22]

As a result, the payback scheme fails to increase the seller's revenue, which differs from the theoretical model prediction. However, we find that the seller's revenue can be increased in the standard first-price auction if the subjects have experienced the payback scheme before. Therefore, even if the payback scheme itself does not enhance the revenue, including this scheme as a trial session before the standard first-price auctions, will give the subjects the inertia to submit a higher bid.

Having addressed the revenue comparison between treatments, next we look at the second measurement - allocation efficiency for the two treatments. To determine the allocation efficiency, we compute the following equation which represents the percentage of surplus captured by an auction mechanism

[22] This suggests that the Pooled OLS model is superior to the random effect model.

$$e = \frac{pv_{winner}}{pv_{highest}} \tag{5.3}$$

where pv_{winner} stands for the winner's private value and $pv_{highest}$ is the highest private value. We report the corresponding results in the last column of Table 5.2. On average, the auction is more efficient in the k0 treatment for both market sizes. This is not surprising, because in the payback scheme auction, the bidders can bid up to their private values plus \$5. It gives the bidder an opportunity to win the auction who uses a larger proportion of the \$5 when submitting his bid, even though his private value is not the highest.

6 Risk preferences in different institutions – first-price auctions and BDM lottery

A number of papers (such as Isaac & James, 2000; Neugebauer & Selten, 2006) identified an overbidding phenomenon and use risk aversion to explain it. In addition, they find out what is the individual's risk preference parameter r in first-price auctions.

In this section, we will qualitatively compare the risk parameters for each group within our two experimental institutions: the first-price auction and the BDM lottery. Here, 'first-price auction' refers to the k0 treatment only. As we have shown in Section 5.1, for the k5 treatment, the estimated intercept of the bid function is significantly less than k, which goes against the RASNE and the LASNE predictions. Following Isaac and James (2000), Engel (2009), and Neugebauer and Selten (2006), we back out the risk parameter r_i using the observations of bids and private values for the specific market size within the RASNE model. However, unlike these papers, we do so for each group instead of each subject.

This is because in this paper our homogeneous risk preference assumption is different from their heterogeneity assumption.[23]

We have derived the RASNE bidding strategy in the standard first-price auction as follows

$$b(v_i) = \frac{n-1}{n+r-1} v_i \tag{6.1}$$

Therefore, the bid data is used to estimate the linear bid function below, and we remove the ‘zero’ bids from the observations.

$$b_i = \alpha_i + \beta_i p v_i + e_i \tag{6.2}$$

Where under the RASNE model, the prediction is that $\alpha_i = 0, \beta_i = \frac{n-1}{n+r-1}$, from which we can obtain the group risk preference parameter r as follows:

$$r = \frac{(1-\beta_i)(n-1)}{\beta_i} \tag{6.3}$$

In our data presentation, we restrict our attention to those bidder groups which satisfy the equilibrium condition that α_i is not significantly different from zero. We report the results of the estimated group risk preference parameters using equation (6.3) in Table 6.1. As can be seen from the table, the estimated intercepts in groups 7 and 9 are significantly positive. Therefore, we do not consider the risk parameters in these two groups. Within the eight groups for which the risk preference parameters r can be estimated, most groups

[23] However, we acknowledge that our experiment design does not guarantee this assumption holds since the subjects formed in one group are randomly chosen.

display different levels of risk aversion in the auction task.[24] In Table 6.1, we also report the corresponding results from the BDM lottery task. As we have shown in Section 4.2, most groups are risk loving in the BDM lottery stage. Overall, our study confirms the instability of risk parameters across different institutions as widely observed by a number of papers, e.g. Isaac and James (2000), Anderson and Mellor (2009), and Hey, Morone, and Schmidt (2009).[25]

[24] We use the same classification as in Section 4.2.
[25] Different from Isaac and James (2000), which also reported the instability of risk preferences between the first-price auction task and the BDM selling procedure, Anderson and Mellor (2009) identify the instability between monetary rewards experiment and a job-based gambles survey; Hey, Morone and Schmidt (2009) report such instability across four incentive-compatible elicitation methods.

Table 6.1 Risk preference parameters in the auction and BDM tasks for each group

	Auction task (k=0)					BDM task	
Group	$\hat{\alpha}$	$\hat{\beta}$	$\hat{r}$	Classification	# Obs.	r_mean	Classification
1	0.126	0.861*	0.807	slightly risk averse	114	1.043	risk neutral
2	-0.325	0.882*	0.669	slightly risk averse	102	0.701	slightly risk averse
3	-0.115	0.835*	0.988	risk neutral	113	1.340	risk loving
4	-0.180	0.888*	0.631	slightly risk averse	107	1.126	risk neutral
5	0.102	0.907*	0.513	risk averse	114	1.221	risk loving
6	-0.051	0.951*	0.258	very risk averse	111	1.407	risk loving
7	0.210*	0.646*	n.a.	n.a.	117	2.519	highly risk loving
8	-0.321	0.756*	0.646	slightly risk averse	113	1.850	very risk loving
9	0.388*	0.748*	n.a.	n.a.	106	1.614	very risk loving
10	0.211	0.800*	0.500	risk averse	115	3.990	highly risk loving

*Note: *significant at 5%. Each group includes 6 subjects who submit bids for 20 rounds in standard auctions, so there are* $6 \times 20 = 120$ *observations for each group. After censoring the 'zero' bids, as shown in the column '#Obs.', the applicable number of observations is less than* 120 *for each group in the standard auction task.*

7 Relevant research

Delgado, Schotter, Ozbay, and Phelps (2008) report a similar experimental design which combines neuroeconomic and behavioural economic techniques. Behavioural economic techniques analyse subjects' experimental decisions to test theoretical predictions. The neuroeconomic approach extends this field by adding observations from the nervous system. Using the finding of neural circuitry, they conjecture that by 'manipulating the parameters of a first-price auction to highlight the potential for loss, it would not only increase bids, but also raise more revenue.' Therefore, they conduct three treatments in a first-price auction format: baseline, loss-frame, and bonus-frame.

We report the differences of the experimental designs between this paper and their article in Table 7.1. Delgado et al. (2008) adopt a between-subject design, which means each subject only participates in one treatment. Another major difference is that in their experiment, the amount of initial capital balance K given to each subject before the auction starts is only 15% relative to the maximum private value, compared with 50% in our experiment.

Table 7.1 First-price auction experimental designs in this paper and in Delgado et al. (2008).

	Our Experiment		Delgado et al. (2008)		
Treatment	Standard	Payback scheme	Baseline	Loss-frame	Bonus-frame
K	0	5	0	15	15
Randomisation technique	Within-subject		Between-subject		
N (Matching method)	6 (Partner) 3 (Partner+Random)		2 (Random)		
Rounds	20		30		
PV	AUD[0,10]		[0, 100] Experimental dollars		

Note: In Delgado et al. (2008), $1 USD = 60 experimental dollars.

The main finding of their experiment is that the seller's revenue is higher in the 'loss-frame' treatment compared with the baseline treatment. Such results are very intriguing since in our experiment, the seller's revenue is significantly smaller in the payback scheme auction relative to the standard first-price auction for the 6-bidder market, and not significantly different for the 3-bidder market, as we illustrated in section 5.2. In order to explore the reason why the schemes affect revenue differently, we compare Delgado et al.'s (2008) experiment results with our findings by re-estimating the bidding functions through normalized bids and private values in the unit interval, and also removing all the 'zero' bids. Here, by pooling all the observations in the same market size and treatment together while ignoring the order effect, we report the corresponding results in Table 7.2.

We need to mention that we could only obtain the bid data of 34 out of the 52 subjects who participated in the 'loss-frame' treatment in Delgado et al. (2008). Using the available data, we obtain similar results to those reported by Delgado et al. (2008) – after normalizing, the average revenue is 0.456 and the random effect bid function is $b = 0.111 + 0.74pv$. However, analysis of the baseline treatment in Delgado et al. (2008), due to the missing data issue could not be undertaken. Therefore, we choose to report the baseline treatment regression results as Delgado et al. (2008) provided in their paper.

Table 7.2 The mean revenue and estimated random effect bid functions from our experiment and Delgado et al. (2008)'s experiment

n		standard FP auction	payback scheme FP auction
2	Revenue	0.409	0.454
	RNNE bid	b*=0.500pv	b*=0.150+0.500pv
	Estimated Bid	b=0.614pv	b=0.109+0.733pv
	# Obs.	660	1018
	R^2	0.805	0.757
3	Revenue	0.571	0.526
	RNNE bid	b*= 0.67pv	b*=0.500+0.67pv
	Estimated Bid	b=0.740pv	b=0.387+0.810pv
	# Obs.	451	480
	R^2	0.862	0.631
6	Revenue	0.766	0.728
	RNNE bid	b*= 0.83pv	b*=0.500+0.83pv
	Estimated Bid	b=0.886pv	b=0.430+0.896pv
	# Obs.	661	681
	R^2	0.945	0.745

Note: 'FP auction' indicates first-price auction. In Delgado et al. (2008), 'standard FP auction' refers to the baseline treatment whereas 'payback scheme FP auction' refers to the loss-frame treatment. The figure of '# Obs.' in each market size for the corresponding treatment is obtained by deleting all the 'zero' bids from the total number of bids.

Table 7.2 clearly shows a common pattern for the estimated bid functions in our experiment and Delgado et al. (2008)'s experiment. That is, in the payback scheme first-price auctions, the estimated bid intercepts are always significantly below the RNNE predictions. With regards to the bid slopes, they are all greater in the payback scheme first-price auctions than the standard first-price auctions, but are only significantly greater in Delgado et al. (2008)'s experiment with a 2-bidder market. Therefore, by comparing the corresponding estimated bid intercepts and slopes, we obtain two possible explanations of the different revenue results within the payback scheme first-price auctions. Considering that the estimated intercept would be always smaller than K, a necessary requirement of the payback scheme enhancing the seller's revenue is that the slope coefficient must be substantially greater compared with that in the standard first-price auction. This is quite unlikely in the larger market sizes, because as market size increases, the slope coefficient already gets closer and closer to 1, and hence does not have much room to keep increasing.

Compared with market size, determining a proper amount of initial capital balance K is likely to play a more important role in whether the scheme enhances the seller's revenue. We can see from both the experiment results that, such a scheme no doubt increases bids regardless of the amount of K. However, in our experiment, K is set too high (50%) relative to the maximum possible private value $\overline{v}$. Hence, even though bids increase due to the payback scheme, they increase by less than K and hence revenue decreases.

As a result, by combining the results of Delgado et al. (2008) experiment with our findings, we obtain the following two conditions, under which the seller's revenue may increase in a payback scheme first-price auction:

- Small market size
- Initial capital balance $K < 0.5\,\overline{v}$.

8 Concluding remarks

The purpose of this paper is to examine whether a payback scheme in first-price private value auctions could enhance seller's revenue due to the existence of loss aversion. We derive a simple single-unit first-price private value auction model, which encompasses two cases - bidders display a homogeneous risk averse attitude or loss averse attitude. Based on the model, the payback scheme should increase the revenue if subjects are loss averse whereas it should not make a difference when subjects are risk averse.

We design an auction experiment using within-subject variation. Each subject participates in two treatments: payback scheme (k5) and standard first-price auction (k0). We also take the order effect into consideration and conduct the experiment with k0k5 and k5k0 orders in two market sizes (6-bidder and 3-bidder). However, the experimental results do not support the hypothesis. More specifically, the revenue within the payback scheme is statistically less than in the standard auction in the 6-bidder market and is not significantly different in the 3-bidder market. Nonetheless, the revenue in the standard auction is increased when subjects have experienced the payback scheme first.

We suggest that the reason the payback scheme fails to enhance revenue in our experiment is that the subjects simply use a certain proportion of the initial capital balance K when submitting bids regardless of private value, and are not induced to respond more strongly to a marginal increase in private value. This is reflected in the intercept of the bidding function increasing by less than K and the slope not changing significantly. Therefore, although the subjects submit higher bids, this does not offset the cost of the initial capital balance K retained by the winner. Combined with the results reported by Delgado et al. (2008) in which the revenue is increased in the 'loss-frame' treatment, a natural extension to our experiments in the future is to set a smaller K (e.g. $1.5) and to test if the payback scheme works or not.

With regards to the experimental design, the future study could also implement another treatment in which only the winner obtains the money K, whereas all the losers receive nothing. Such an auction design is strategically equivalent to the payback scheme, and it would be interesting to compare the results to this paper. There is also some scope for future research to extend the theoretical framework to incorporate reference-dependent preferences.

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Appendix A

Welcome to the experiment!

You will receive a show-up payment of $10 for participating in this experiment which consists of four independent parts. For each of these four parts, you will be given written instructions which will be read aloud.

In each part of the experiment, you will get a payoff which will depend both on your decisions and on chance.

To determine your earnings for participating in this experiment, the payoffs you get in these four parts will be added to your show-up payment of $10.

Note that in Part 1, your payoff may be positive or negative. Positive payoffs are added to your show-up fee of $10 whereas negative payoffs are subtracted from it.

You are not allowed to communicate with other participants during the experiment.

If you have any questions, please raise your hand and someone will answer your questions individually.

If you have no questions, then please proceed to reading the instructions for Part 1.

Part 1: lotteries

In this first part, you are asked to answer fourteen questions. Each of these questions asks whether you want to participate or not in a lottery which yields a **win** (in dollars) with **50%** chance and a **loss** (in dollars) with **50%** chance. If you would like to participate in the proposed lottery, please select "Yes" or if you do not wish to, then select "No". Each of the fourteen questions relates to a different lottery for which you have to decide whether to participate or not by answering "Yes" or "No".

At the end of the experiment, **one** of the fourteen questions will be randomly selected to determine your payoff for participating in this first part. If you answered "Yes" to the selected question, then you will participate in the selected lottery and your payoff for participating in this first part will be equal to the outcome of this lottery. If you selected "No" then you will not participate in the selected lottery and your payoff for this first part will be $0.

Example: *suppose that **at the end of the experiment**, question 3 is drawn. Assume that question 3 asked whether you want to participate in a lottery in which you can either win $X with 50% chance or lose $Y with 50% chance.*

If you answered "Yes" to question 3, then your payoff for participating in this first part will be the outcome of the proposed lottery. It can either be a gain of $X or a loss of $Y.

If you answered "No" to question 3, then your payoff for participating in this first part will be $0.

If you have any questions, please raise your hand and someone will answer your questions individually.

If you have no questions, then please answer the following comprehension questions. Note that your answers to these questions do not affect your earnings in any way. The purpose of these questions is just to make sure that you understand the game you are about to play.

Part 2: selling a lottery ticket

In this second part, you are the owner of eleven lottery tickets. Each of these lottery tickets yields a high payoff with 50% chance or a low payoff with 50% chance, and you are given an opportunity to sell the tickets.

If you want to sell your lottery ticket, then you must state a 'selling price' between the low payoff and the high payoff (which can be equal to the low or high payoff). A 'selling price' is the minimum price at which you are willing to sell your lottery ticket.

The buyer of your lottery ticket is played by the computer which has been programmed to make a random 'buying price' between the low payoff and the high payoff (inclusive). This means that the computer can offer any 'buying price' between the low payoff and the high payoff (inclusive) with equal chance. Note that the computer's 'buying price' does not depend in any way on your 'selling price' and that it can have up to two decimals.

At the end of the experiment, **one** of the eleven lottery tickets will be randomly selected to determine your payoff for participating in this second part.

There are two possible outcomes:

- First, your 'selling price' is greater than the computer's 'buying price'. In this case, you do not sell your lottery ticket and your payoff, which will be determined **at the end of the experiment**, will be equal to the outcome of the lottery. That is, you will either earn the high payoff with 50% chance or the low payoff with 50% chance.
- Second, your 'selling price' is smaller or equal to the computer's 'buying price'. In this case, you do sell your lottery ticket and your payoff will be equal to the computer's 'buying price'.

Example: *suppose that* ***at the end of the experiment****, lottery 5 is drawn. Assume that in this lottery you can either gain $7 with 50% chance or gain $2 with 50% chance and you state $4 as the 'selling price'.*

If the computer's 'buying price' is $5, then you sell your lottery ticket to the computer and your payoff for participating in this second part will be equal to $5.

If, on the other hand, it turns out that the computer's 'buying price' is $3, then you keep your lottery ticket and your payoff for participating in this second part will be equal to the outcome of the lottery, that is, you will either receive a payoff of $7 with 50% chance or of $2 with 50% chance.

If you have any questions, please raise your hand and someone will answer your questions individually.

If you have no questions, then please answer the following comprehension questions. Note that your answers to these questions do not affect your earnings in any way. The purpose of these questions is just to make sure that you understand the game you are about to play.

Part 3: Auction I

In this third part, you are competing in a market with six buyers and you are one of them. The other five buyers are other participants in this lab.

You are participating in 20 auctions with the same group of buyers.

At the beginning of each auction, the computer will randomly determine a value for you, which may be any cent amount between and including $0.00 and $10.00, with each amount in this interval being equally likely to be chosen.

The values for other bidders are also randomly drawn, with each cent amount between $0.00 and $10.00 being equally likely.

Your value will be independent of any other buyer's value and is also independent of your own value in other auctions.

You can submit any bid up to *your value* (with up to two decimals). If you do not want to participate in this auction, then you must submit a bid of $0.

If you submit the highest bid then you win the auction. In this case, you pay a price equal to your bid and get the following payoff:

Your payoff = your value - your bid (if you win)

If your bid is not the highest then you lose the auction. In this case, you get the following payoff:

Your payoff = 0 (if you lose)

If there is no single highest bid, then one of the equal highest bidders will be randomly determined as the winner of the auction.

At the end of each auction, you will find out whether you have won or lost the auction, the payoff you have, and what is the highest bid.

At the end of the experiment, **two** of the 20 auctions will be randomly selected to determine your payoff for participating in this third part.

Example: *suppose that* ***at the end of the experiment****, auctions 6 and 12 are drawn and your payoffs for the two auctions are the following:* *Auction 6: \$A* *Auction 12: \$B* *Your earnings from this third part will be equal to: \$A+\$B.*
Assume that in auction 6, you have a value of \$ 9, and you submit a bid of \$ 6. *If you are the winner, your payoff for participating in auction 6 is \$9-\$6 = \$3.* *If you lose the auction, your payoff for participating in auction 6 is \$0.*

If you have any questions, please raise your hand and someone will answer your questions individually.

If you have no questions, then please answer the following comprehension questions. Note that your answers to these questions do not affect your earnings in any way. The purpose of these questions is just to make sure that you understand the game you are about to play.

Part 4: Auction II

In this fourth and last part, you are participating in 20 auctions with the same group of buyers as in part 3.

The basic setting for this part is the same as in part 3, which is:

At the beginning of each auction, the computer will randomly determine a value for you, which may be any cent amount between and including \$0.00 and \$10.00, with each amount in this interval being equally likely to be chosen.

The values for other bidders are also randomly drawn, with each cent amount between \$0.00 and \$10.00 being equally likely.

Your value will be independent of any other buyer's value and is also independent of your own value in other auctions.

The difference in this part is:

At the beginning of each auction, you are given \$5.

Your bid can be any cent amount up to <u>your value plus $5</u>. If you do not want to participate in this auction, then you must submit a bid of $0.

If you submit the highest bid then you win the auction. In this case, you **keep the $5** and pay a price equal to your bid. Your payoff is defined as follows:

Your payoff = $5 + your value – your bid (if you win)

If your bid is not the highest then you lose the auction. In this case, you must **give the $5 back.** Your payoff is defined as follows:

Your payoff = $5- $5= 0 (if you lose)

If there is no single highest bid, then one of the equal highest bidders will be randomly determined as the winner of the auction.

At the end of each auction, you will find out whether you have won or lost the auction, the payoff you have, and what is the highest bid.

At the end of the experiment, **two** of the 20 auctions will be randomly selected to determine your payoff for participating in this fourth part.

*Suppose that **at the end of the experiment**, auctions 6 and 12 are drawn and your payoffs for the two auctions are the following:*

Auction 6: $A

Auction 12: $B

Your earnings from this fourth part will be equal to: $A+$B.

***Example 1:** Assume that in auction 6, you have a value of $ 9, and you submit a bid of $ 6.*

If you are the winner, you keep the $5, so your payoff for auction 6 is $5+$9-$6= $8.

If you lose the auction, then you must pay the $5 back, so your payoff for auction 6 is $5-$5=$0.

***Example 2:** Assume that in auction 6, you have a value of $ 9, and you submit a bid of $ 12.*

If you are the winner, you keep the $5, so your payoff for auction 6 is $5+$9-$12= $2.

If you lose the auction, then you must pay the $5 back, so your payoff for auction 6 is $5-$5=$0.

If you have any questions, please raise your hand and someone will answer your questions individually.

If you have no questions, then please answer the following comprehension questions. Note that your answers to these questions do not affect your earnings in any way. The purpose of these questions is just to make sure that you understand the game you are about to play.

Appendix B

The following equation is the first-order differentiation equation of Risk Averse symmetric Nash equilibrium (RASNE) bidding strategy.

$$b'(v_i) = \frac{(n-1)(K + v_i - b(v_i))}{v_i r}$$

$$b'(v_i) = -\frac{(n-1)b(v_i)}{v_i r} + \frac{n-1}{r} + \frac{(n-1)K}{v_i r} \qquad \text{(B.1)}$$

Let $p(v_i) = \frac{n-1}{v_i r}$, $q(v_i) = \frac{n-1}{r} + \frac{(n-1)K}{v_i r}$ and they are known by the bidders.

Therefore we can write equation (B.1) as follows

$$b'(v_i) + p(v_i)b(v_i) = q(v_i)$$

Multiplying each side by an integrating factor $m(v)$, which yields

$$m(v)b'(v_i) + m(v)p(v_i)b(v_i) = m(v)q(v_i) \qquad \text{(B.2)}$$

And also in particular we require

$$m(v)b'(v_i) + m(v)p(v_i)b(v_i) = [m(v)b(v_i)]'$$

So, equation (B.2) becomes

$$[m(v)b(v_i)]' = m(v)q(v_i) \qquad \text{(B.3)}$$

Which implies that $m'(v) = p(v_i)m(v)$

We know that $m'(v) = \frac{dm}{dv}$, so $\frac{dm}{dv} = p(v_i)m(v)$

$$\frac{dm}{m} = p(v_i)dv$$

Integrating both sides y

$$\ln m(v) = \int_0^v p(t)dt$$

$$m(v) = \exp[\int_0^v p(t)dt] = \exp[\frac{n-1}{r}\int_0^v \frac{1}{t}dt] = \exp\left[\frac{n-1}{r}\cdot \ln v\right] = (e^{\ln v})^{\frac{n-1}{r}} = v^{\frac{n-1}{r}}$$

Integrating both sides for equation (B.3)

$$m(v)b(v_i) = \int_0^v m(t)q(t)dt$$

$$b(v_i) = \frac{1}{m(v)}\int_0^v m(t)q(t)dt$$

$$= \frac{1}{v^{\frac{n-1}{r}}}\int_0^v t^{\frac{n-1}{r}}\left(\frac{n-1}{r} + \frac{(n-1)K}{tr}\right)dt$$

$$= \frac{1}{v^{\frac{n-1}{r}}}[\frac{n-1}{r}\int_0^v t^{\frac{n-1}{r}}dt + \frac{(n-1)K}{r}\int_0^v t^{\frac{n-1}{r}-1}dt]$$

$$= \frac{1}{v^{\frac{n-1}{r}}}[\frac{n-1}{r}\cdot\frac{v^{\frac{n-1}{r}+1}}{\frac{n-1}{r}+1} + \frac{(n-1)K}{r}\frac{v^{\frac{n-1}{r}}}{\frac{n-1}{r}}]$$

$$= \frac{n-1}{n-1+r}\, v + K$$