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Loss Aversion and Competition in Vickrey Auctions: Money Ain't No Good*

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Abstract

We present results from an experiment with a within-subject design aimed at testing a unique prediction of expectations-based reference-dependent preferences and loss aversion in private-value second-price (Vickrey) auctions. If bidders have expectations-based reference-dependent preferences, the total number of participants in an auction should affect bids in auctions for real objects but not in auctions with induced monetary values. Our findings are consistent with expectations-based reference-dependent preferences and loss aversion. In real-object auctions, subjects' bids are affected by the number of competitors and, on average, they decline with the intensity of competition. In induced-value auctions, instead, bids are unaffected by the intensity of competition. We also successfully replicate an experiment from Sprenger (2015) aimed at distinguishing expectations-based loss aversion from models of Disappointment Aversion. This provides additional evidence that our findings in the auction experiments are due to expectations-based loss aversion.

JEL Classification: C91; C92; D03; D44; D81; D84

Keywords: Auctions; Reference-Dependent Preferences; Loss Aversion; Expectations.

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1 Introduction

The second-price sealed-bid auction, first introduced in Vickrey's (1961) seminal paper and hence also known as simply the Vickrey auction, is probably the most famous and easily understood auction format from a theoretical point of view. It is well-known that in standard private-value auction models of fully rational bidders with standard preferences, bidding one's own value is a (weakly) dominant strategy. This theoretical prediction holds irrespective of bidders' risk attitudes, the number of bidders in the auction, symmetry (or lack thereof) in the values' distributions or whether the values are correlated. Moreover, this prediction is very robust in the sense that it continues to hold also in models where bidders have non-standard (risk) preferences, i.e. anticipated regret as in Ozbay and Ozbay (2007) or ambiguity aversion as in Chen *et al.* (2007), or where bidders are not perfectly rational as in Crawford and Iriberri's (2007) analysis of level-k auctions.

However, as shown by Lange and Ratan (2010), if bidders have expectations-based reference-dependent preferences à la Köszegi and Rabin (2006, 2007) (henceforth, KR), bidding one's own value is not a dominant strategy anymore. This occurs because his competitors' strategy directly affect a bidder's beliefs about his likelihood of winning the auction and hence his reference point. Moreover, the KR model makes different predictions in auctions for real objects than in auctions with induced monetary values, the latter being the type of auctions commonly run in most laboratory experiments. In particular, in real-object auctions equilibrium bids should vary with the intensity of competition. Intuitively, when the number of competitors in the auction increases, *ceteris paribus* a bidder expects to win with a lower probability; this in turn will induce a loss-averse bidder to bid less, for a large interval of intrinsic values for the object. In induced-value auctions, instead, in the (unique) symmetric equilibrium bidders bid their value. The reason for this discrepancy in the equilibrium bids between real-object and induced-value auctions is as follows. In an auction for a real object bidders trade off feelings of loss and gain across different dimensions. For example, losing the auction feels like a loss in the product dimension and, at the same time, as a gain in money compared to the possibility of winning the auction. Therefore, it is not possible for the bidder to eliminate losses on both dimensions simultaneously. In induced-value auctions, on the other hand, there is only one dimension of consumption utility, namely money, and hence losing (resp. winning) the auction always feels like a loss (resp. gain).[1]

In this paper we present evidence from a laboratory experiment with a within-subject design aimed at testing the comparative statics predictions of expectations-based reference-dependent preferences and loss aversion in second-price private-value auctions. In the experiment, subjects took part in auctions for real objects as well as auctions with induced

[1]The notion that bidders, or people more generally, assess gains and losses separately across the different dimensions of consumption utility is related to the concept of mental (or psychological) accounting; see Thaler (1985, 1999).

monetary values. For each "prize" a subject participated in three separate auctions, each time facing a different yet known number of rivals. This design allows us to see whether and how a participant's bid for a given prize changes depending on how many rivals he is facing and also to compare these changes for real-object auctions vs. induced-value ones.

Our findings are consistent with the predictions of the KR model. For real-object auctions we find that increasing the intensity of competition pushes bidders to reduce their bids on average. In particular, when the number of bidders increases from three to twelve, bids decline by 6%. The effect almost doubles when restricting attention to those subjects who express a strong desire in obtaining the good. As it could be expected, there is substantial heterogeneity in how participants respond to changes in the number of bidders in an auction. More than half of the participants changed their bids in response to an increase in the number of rivals. While the proportion of subjects who increased their bid when the number of rivals increased is roughly equal to the number of people who reduced their bids, we observe that those reducing their bids do so by a greater amount. In induced-value auctions, instead, we find that the intensity of competition has no significant effect on bids. Besides providing support for the KR model, these results also suggest that bidders may behave differently in real-object auctions than in induced-value ones.

In addition to the primary auction task, subjects in our experiment also completed an individual decision-making task with a between-subject design originally designed by Sprenger (2015). The aim of this individual-decision making task is to distinguish the KR model from expectations-based models of Disappointment Aversion (Bell, 1985; Loomes and Sudgen, 1986; Gul, 1991). The KR model predicts that when risk is expected, and therefore the reference point is stochastic, behavior will be different from when risk is unexpected and the reference point is deterministic. In particular, when the reference point is stochastic, and an individual is offered a certain amount, the KR model predicts near risk neutrality. Conversely, when the reference point is a fixed certain amount, and an individual is offered a gamble, the KR model predicts risk aversion. Hence, the KR model features an endowment effect for risk. Disappointment aversion makes no such asymmetric prediction as to the relationship between risk attitudes and reference points, because gambles are always evaluated relative to a deterministic reference point, that is the gamble's certainty equivalent. Successfully replicating the results in Sprenger (2015), we find evidence of an endowment effect for risk which provides support for the KR model. We interpret the results from this individual decision-making task as additional evidence that our findings in the primary auction experiment are due to expectations-based loss aversion.

Our theoretical framework builds on the work of Lange and Ratan (2010) who theoretically analyze first-price and second-price sealed-bid auctions with expectations-based loss-averse bidders. They were the first to show that the predictions of the KR model vary depending on whether the auction analyzed is a real-object one or an induced-value one, pointing out that transferring qualitative behavioral findings from induced-value laboratory experiments to the field may be problematic if subjects are expectations-based loss-averse.[2]

Our paper is related to Banerji and Gupta (2014) who provide evidence in favor of the KR model in an auction-like experiment using the Becker-DeGroot-Marschak (henceforth, BDM) mechanism (Becker, DeGroot and Marschak, 1964). In a BDM auction, a single bidder competes against a random bid drawn from a known distribution. If his bid beats the random draw, he wins the prize and pays a price equal to the random draw; if his bid is lower, on the other hand, he loses. It is easy to see that if preferences are standard, this is an incentive-compatible mechanism (i.e., it is optimal to bid one's value for the prize).[3] Yet, if a bidder has expectations-based reference-dependent preferences, it is in general not optimal to bid one's value in a BDM auction. Their experimental design exogenously manipulates the expectations-based reference point by assigning subjects to one of two treatments: individuals bid against uniform distributions with supports $[0, K_1]$ in one treatment and $[0, K_2]$ in the other, with $K_2 > K_1$. The KR model predicts that when the prize is a real object, bids in the first treatment will stochastically dominate bids in the second one whereas no significant differences in the distributions of bids should be observed for induced-value auctions. Their results confirm the predictions of the KR model. Despite these similarities, there are three main differences between our paper and theirs. First, while their experiment has a between-subject design, our experiment has a within-subject design whereby each subject bids for the same prize three times, each time facing a different number of rival bidders. This allows us to perform a direct test of the comparative statics predictions of the KR model. Second, they run their experiment with only one real good (a bar of dark chocolate) whereas we have subjects bidding on three goods, all of which are not perishable and are rather expensive and appealing. Last, their experiment looks at the BDM mechanism which does not posses any element of strategic interaction; while under standard preferences BDM is strategically equivalent to a second-price auction, it is not clear *a priori* whether the predictions of the KR model would continue to hold in an environment with strategic interaction. Our experiment, on the other hand, is a second-price auction where subjects' payoffs depend on the behavior of their competitors.[4] More generally, our paper contributes to the recent and growing literature testing the predictions of the KR model of expectations-based reference-dependent preferences and loss aversion. For experimental evidence see, for instance, Abeler

[2]See also the related work by Eisenhuth (2012) who derives the seller's revenue-maximizing mechanism when bidders have KR preferences.

[3]Due to this property, the BDM auction is popular as a mechanism to "elicit" subjects' willingness to pay and accept (WTP/WTA). However, see Cason and Plott (2014), Tymula *et al.* (2013) and Mazar *et al.* (2014) on some of the limitations of the BDM mechanism for consistently eliciting WTP/WTA measures.

[4]Eisenhuth and Ewers (2012) also provide experimental evidence for the KR model in the context of auctions using both real-object and induced-value auctions. Their focus, however, is different than ours as they use a between-subject design and are mainly interested in the revenue comparison between the first-price sealed-bid auction and the all-pay auction.

et al. (2011), Ericson and Fuster (2011), Gill and Prowse (2012), Heffetz and List (2014), Karle *et al.* (2015), Wenner (2015) and Sprenger (2015). For evidence from the field, see Card and Dahl (2011), Crawford and Meng (2011), Pope and Schweitzer (2011) and Bartling *et al.* (2015). Though both positive and negative results have been reported, the literature as whole seems to indicate that expectations do play a role in shaping reference points.

Finally, our paper also contributes to the extensive experimental literature on Vickrey auctions with private values.[5] Several studies have found that subjects deviate from the (weakly) dominant strategy of bidding their values, with overbidding being somewhat more common than underbidding (Kagel *et al.*, 1987; Kagel and Levin, 1993; Harstad, 2000; Cooper and Fang, 2008). By contrast, experimental evidence from the strategically equivalent ascending English auction demonstrates almost immediate convergence to the dominant strategy.[6] Garratt *et al.* (2012) conducted an online experiment with experience bidders who regularly participate in eBay auctions. They compare the frequency of value-bidding in their online experiment with Kagel and Levin's (1993) lab experiment and find similar results: 21.2% in Garratt *et al.* (2012) vs. 27.0% in Kagel and Levin (1993). Yet, there are substantial differences in the nature of the deviations; while overbidding was much more frequent than underbidding in Kagel and Levin (1993) (67.2% vs. 5.7%), Garratt *et al.* (2012) find that the majority of the deviations from value-bidding were underbids (41.3% vs. 37.5%). Kagel *et al.* (1987) conjectured that bidding above one's own value in a second-price auction is based on the illusion that it improves the probability of winning with little cost because the winner only pays the second-highest bid. Exploring this idea further, Georganas *et al.* (2015) look at the effect of introducing monetary penalties for deviations from value-biding. They find that although subjects fail to discover the dominant strategy, they seem to respond to the changes in the degree of penalty. Our paper departs from this literature on two main aspects. First, while all the papers mentioned above consider auctions with induced monetary values, we are the first to analyze second-price auctions with real objects. Second, while the literature's main focus has been on testing whether bidders adopt the dominant strategy of bidding their value, our paper's focus is not on overbidding per se. Instead it uses a within-subject design in order to test the comparative static predictions of the KR model about how individual bids are affected by the degree of competitiveness of the auction.

The paper proceeds as follows. Section 2 presents the theoretical framework. Section 3 describes the experimental design and the data. Section 4 presents the results. Section 5 concludes the paper by discussing some limitations as well as possible avenues for future research.

[5]For excellent surveys of the experimental literature on auctions see Kagel (1995) and Kagel and Levin (forthcoming).

[6]See also the recent contribution by Li (2015) on the notion of "obviously" strategy-proof mechanisms.

2 Theoretical Framework

2.1 Environment

Consider a risk-neutral seller auctioning an object to $n \geq 2$ bidders via a second-price sealed-bid auction. Assume bidders have independent private values.[7] Each bidder's valuation (type) θ_i, for $i = 1, ..., n$, is drawn independently from the same continuous and strictly increasing distribution H which admits a continuous and positive density h everywhere on the support $\left[0, \overline{\theta}\right]$.

Bidders have expectations-based reference-dependent preferences as formulated by Kőszegi and Rabin (2006). In this formulation, a bidder's utility function has two components. First, if he wins the auction at price p, a type-θ bidder experiences *consumption utility* $\theta - p$. Consumption utility can be thought of as the classical notion of outcome-based utility. Second, the bidder also derives utility from the comparison of his actual consumption to a reference point given by his recent expectations (probabilistic beliefs).[8] Hence, for a riskless consumption outcome (θ, p) and riskless expectations $\left(r^{\theta}, r^{p}\right)$, a bidder's total utility is given by

$$U\left[(\theta, p) \mid \left(r^{\theta}, r^{p}\right)\right] = \theta - p + \mu\left(\theta - r^{\theta}\right) + \mu\left(r^{p} - p\right) \tag{1}$$

where

$$\mu(x) = \begin{cases} \eta x & \text{if} \quad x \geq 0 \\ \eta \lambda x & \text{if} \quad x < 0 \end{cases}$$

is *gain-loss utility,* with $\eta > 0$ and $\lambda > 1$. The parameter η captures the relative weight a consumer attaches to gain-loss utility while λ is the coefficient of loss aversion. By positing a constant marginal utility from gains and a constant, but larger marginal disutility from losses, this formulation captures prospect theory's (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991) loss aversion, but without its diminishing sensitivity. According to (1), a bidder assesses gains and losses separately over product and money. For instance, if his reference point is that he will not get the product (and thus pay nothing), then he evaluates getting the product and paying for it as a gain in the product dimension and a loss in the money dimension rather than as a single gain or loss. This is consistent with much of the experimental evidence commonly interpreted in terms of loss aversion.[9]

[7] Independence is not crucial for our results, but it simplifies the analysis.

[8] Recent experimental evidence lends support to Kőszegi and Rabin's (2006, 2007) expectations-based model of reference-dependent preferences and loss aversion; see, for instance, Abeler *et al.* (2011), Ericson and Fuster (2011), Gill and Prowse (2012), Karle *et al.* (2015) and Sprenger (2015). More pertinently, Banerji and Gupta (2014) and Eisenhuth and Ewers (2012) provide experimental evidence supporting the KR model in the context of sealed-bid auctions.

[9] This feature is able to explain the endowment effect observed in many laboratory experiments (see Kahneman *et al.* 1990, 1991). The common explanation of the endowment effect is that owners feel giving up the object as a painful loss that counts more than money they receive in exchange, so that they demand a lot of money for the object. But if gains and losses were defined over the value of the entire transaction, owners

Because in many situations expectations are stochastic, Köszegi and Rabin (2006) extend the utility function in (1) to allow for the reference point to be a pair of probability distributions $\Gamma = \left(\Gamma^{\theta}, \Gamma^{p}\right)$. In this case a bidder's overall utility from the outcome (θ, p) can be written as

$$U\left[(\theta, p) \mid (\Gamma^{v}, \Gamma^{p})\right] = \theta - p + \int_{r^{\theta}} \mu\left(\theta - r^{\theta}\right) d\Gamma^{\theta} + \int_{r^{p}} \mu\left(r^{p} - p\right) d\Gamma^{p} \tag{2}$$

In words, a bidder compares the realized outcome with each possible outcome in the reference lottery. For example, if he expected to win the auction at price p with probability q, then winning the auction feels like a gain of $\eta\theta\,(1-q)$ in the product dimension and a loss of $-\eta\lambda p\,(1-q)$ in the money dimension. Similarly, losing the auction results in a loss of $-\eta\lambda\theta q$ and a gain of ηpq. Thus, the weight on the loss (gain) in the overall experience is equal to the probability with which he was expecting to win (lose) the auction.

Each bidder knows his valuation before submitting his bid and, therefore, maximizes his interim expected utility. If the distribution of the reference point is Γ and the distribution of consumption outcomes is $G = \left(G^{\theta}, G^{p}\right)$, a type-$\theta$ bidder's interim expected utility is given by

$$EU\left[G|\Gamma\right] = \int_{\{\theta,p\}} \int_{\left\{r^{\theta}, r^{p}\right\}} U\left[(\theta, p)\,|r^{\theta}, r^{p}\right] d\Gamma dG.$$

After placing a bid, a bidder basically faces a lottery between winning or losing the auction and the probabilities and potential payoffs depend on his own as well as the other players' bids. The final outcome is then evaluated with respect to any possible outcome from this lottery as a reference point. As laid out in Köszegi and Rabin (2007), Choice Acclimating Personal Equilibrium (*CPE)* is the most appropriate solution concept for such decisions under risk when uncertainty is resolved after the decision is made so that the decision maker's strategy determines the distribution of the reference point as well as the distribution of final consumption outcomes; that is, $\Gamma = G$.[10]

The following assumption, maintained for the remainder of the paper, guarantees that all bidders participate in the auction for any realization of their own type, and that the equilibrium bidding functions derived in the next sections are strictly increasing and continuous:

Assumption 1 (No dominance of gain-loss utility) $\Lambda \equiv \eta\,(\lambda - 1) \leq 1$.

would not be more sensitive to giving up the object than to receiving money in exchange. In particular, using a modification of a standard endowment effect experiment, Ericson and Fuster (2011) demonstrate that individuals with a high experimental probability of being able to exchange are willing to do so with a higher probability than individuals with a low probability of being able to exchange. Notice, however, that using a very similar experimental design, Heffetz and List (2014) fail to replicate the results of Ericson and Fuster (2011).

[10] The notion of CPE in Köszegi and Rabin (2007) is related to the models of "disappointment aversion" of Bell (1985), Loomes and Sugden (1986), and Gul (1991), where outcomes are also evaluated relative to a reference lottery that is identical to the chosen lottery.

This assumption places, for a given η (λ), an upper bound on λ (η) and ensures that a bidder's equilibrium expected utility is increasing in his type.[11] What it requires is that the weight a bidder places on expected gain-loss utility does not (strictly) exceed the weight she puts on consumption utility.[12]

Each agent can place a bid $b \in [0, w]$ where w denotes agents' symmetric monetary endowments or budgets. Throughout the paper, we assume that the budget constraint does not bind and we restrict attention to symmetric equilibria in pure and (strictly) monotone strategies. We consider both real-object and induced-value second-price sealed-bid auctions.

2.2 Real-Object Auctions

For given bidding strategies of the other players let $F(b)$ denote a bidder's probability of winning with a bid equal to b and let $F(p)$ denote the probability of paying a price less or equal to p, conditioning on winning the auction. Then reference-dependent expected utility of a bidder of type θ is given by

$$\begin{aligned} EU(b,\theta) &= \int_{b(0)}^{b} (\theta - p)\, dF(p) - \Lambda\left[1 - F(b)\right] \int_{b(0)}^{b} p dF(p) \\ &\quad -\Lambda \int_{b(0)}^{b} \int_{b(0)}^{p} (p - s)\, dF(s)\, dF(p) - \Lambda \theta F(b)\left[1 - F(b)\right] \end{aligned} \tag{3}$$

The first term on the right-hand-side of (3) is standard expected (consumption) utility. The other terms capture expected gain-loss utility and are derived as follows. The second term captures the expected comparison, on the money dimension, between winning the auction and having to pay p and losing the auction and saving p. The third term reflects the expected comparison, still on the money dimension, between the winning price p and all the other prices s the bidder expects to pay with positive probability. Finally, the last term describes the expected gain-loss utility on the good dimension when expecting to win the auction with probability $F(b)$.[13]

Lange and Ratan (2010) showed that in the unique monotone symmetric equilibrium a

[11] Herweg *et al.* (2010) first introduced Assumption 1 and referred to it as "no dominance of gain-loss utility". Assumption 1 has been used also by Lange and Ratan (2010), Eisenhuth (2012) and Eisenhuth and Ewers (2012).

[12] Eisenhuth and Ewers (2012), using data from first-price and all-pay auctions with induced monetary values, obtain an estimate for Λ of 0.42 (with a standard error of 0.16), which is statistically different from 0 and 1 at all conventional significance levels. Using data from a BDM-like auction for real products (chocolate bars), Banerji and Gupta (2014) obtain an estimate for Λ of 0.283 (with a standard error of 0.08), also statistically different from 0 and 1 at all conventional significance levels.

[13] Notice that risk neutrality is embedded in the model as a special case since $\Lambda = 0$ for either $\eta = 0$ or $\lambda = 1$.

bidder of type θ bids according to the following bidding function:

$$\beta^*(\theta,n) = \theta\left\{\frac{1-\Lambda\left[1-2H^{n-1}(\theta)\right]}{1+\Lambda}\right\} + \frac{2\Lambda}{(1+\Lambda)^2}\int_0^\theta z\left\{1-\Lambda\left[1-2H^{n-1}(z)\right]\right\}\exp\left\{\frac{2\Lambda\left[H^{n-1}(\theta)-H^{n-1}(z)\right]}{1+\Lambda}\right\}dH^{n-1}(z). \tag{4}$$

It is easy to see that a player's equilibrium bid depends on the number of bidders. Yet, it is well-known that for a bidder with expected-utility preferences it is weakly-dominant to submit a bid equal to his intrinsic value for the item, no matter how many competitors he faces.[14] Moreover, it is still a weakly-dominant strategy for a bidder to bid his value if he is regret-averse (Ozbay and Ozbay, 2007) or ambiguity-averse (Chen *et al.*, 2007). Similarly, level-k models also predict that in second-price auctions with private values bidders will bid truthfully (Crawford and Iriberri, 2007). Furthermore, the two most common explanations for the deviation from value-bidding in second-price auctions laboratory experiments, the spite hypothesis and the "joy of winning"hypothesis, do not predict that individual bids should vary with the intensity of competition. Indeed, while these hypotheses predict that bidders would bid more than their intrinsic value, the amount of overbid is independent of the number of bidders in the auction (see Morgan *et al.*, 2003 and Cooper and Fang, 2008). Therefore, the comparative statics with respect to n represent a unique and distinctive prediction of the expectations-based model of reference-dependent preferences. Moreover, as shown by Banerji and Gupta (2014), if Assumption 1 holds, we have that $\frac{\partial\beta^*(\theta,n)}{\partial n} < 0$ for all θ such that $\log(H(\theta)) < -\frac{1}{n-1}$. This (sufficient) condition implies, for example, that if two auctions in this symmetric setting have $n = 6$ and $n' = 12$ bidders respectively, then all bidders whose values fall within the lowest 82 percent of the distribution of values will bid less when the number of bidders is larger. Conversely, bidders whose values are in the top 18 percent of the distribution of values will bid more when the number of bidders is larger. The intuition is as follows. When the number of bidders in the auction increases, *ceteris paribus* a bidder expects to win with a lower probability. Low-value bidders already expect to win with a rather small probability to begin with and so they react to the increase in competition by reducing their bid in order to keep their expectations low and therefore reducing their feelings of loss from not winning the auction (but making a big splash if they do win). On the other hand, high-value bidders expect to win the auction with a rather high probability and, therefore, they react to an increase in competition by bidding even more aggressively in order to reduce the chance of experiencing a loss from not obtaining the object. Thus varying the number of bidders can be used to identify expectations-based reference-dependent preferences in second-price auctions with loss-averse bidders. Figure 1

[14] This prediction holds irrespective of the bidder's attitudes towards risk and of the structure of correlation between the bidders' values.

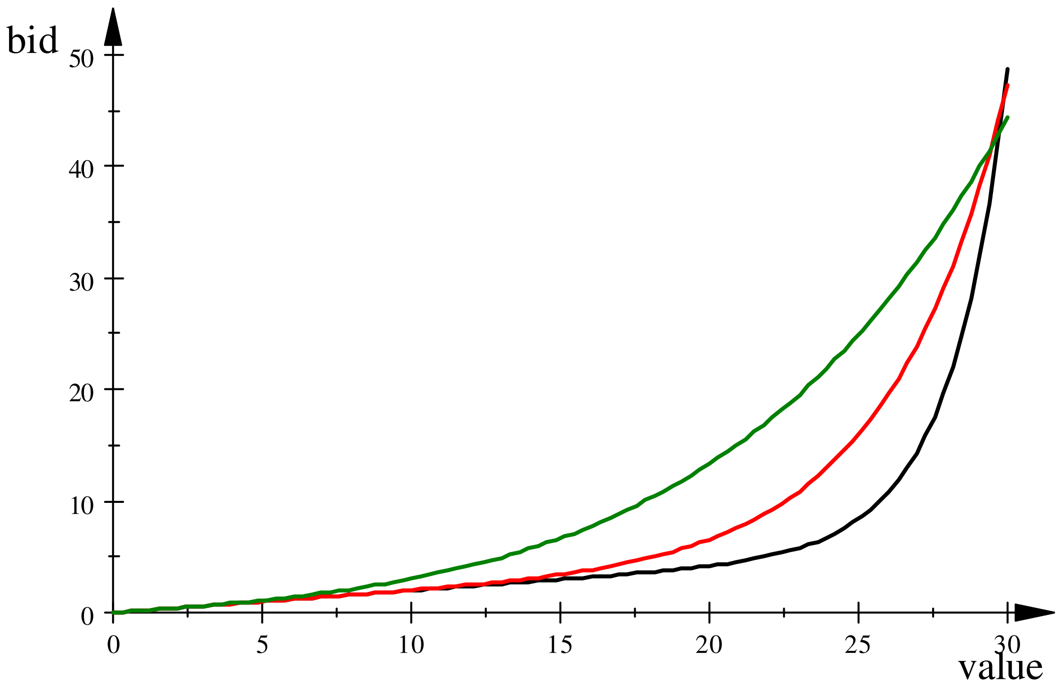


Figure 1: Equilibrium bidding functions for $n = 3$ (green), 6 (red) and 12 (black) with $\Lambda = (2/3)$ and θ distributed uniformly on $[0, 30]$.

provides a graphical example to illustrate the comparative statics with respect to the number of bidders of the equilibrium bidding function under loss aversion. It is easy to see that as n increases, the average bid declines.

2.3 Induced-Value Auctions

In an auction with induced monetary values each subject is given a voucher and, if he wins the auction, he can redeem the voucher from the experimenter in exchange of a pre-specified dollar amount, say $\$\theta$. Hence, his intrinsic payoff is $\theta - p$ if he wins the auction at price p and zero otherwise. Again, let $F(p)$ denote the probability of paying a price less or equal to p, conditioning on winning the auction. Crucially, in an auction with induced monetary values there is only one dimension of consumption utility, namely money. Then, the reference-dependent expected utility of a bidder of type θ is given by

$$\begin{aligned} EU_{IV}(b, \theta) &= \int_{b(0)}^{b} (\theta - p)\, dF(p) - \Lambda [1 - F(b)] \int_{b(0)}^{b} (\theta - p)\, dF(p) \\ &\quad -\Lambda \int_{b(0)}^{b} \int_{b(0)}^{p} (p - s)\, dF(s)\, dF(p). \end{aligned} \tag{5}$$

The first term on the right-hand-side of (5) represents standard expected (consumption) utility. The second term captures the expected gain-loss utility when comparing the outcome of winning the auction, which yields an expected monetary payoff of $\int_{b(0)}^{b} (\theta - p)\, dF(p)$, and the outcome of losing the auction, which yields a payoff of 0. Finally, the last term reflects the expected gain-loss utility when comparing winning the auction at price p and winning at all the other prices s which the bidder expects to pay with positive probability.

The bidding strategy of a loss-averse bidder in an induced-value auction is quite different from his strategy in a real-object auction. The reason is that in an auction for a real object the bidder trades off feelings of loss and gain across different dimensions — for example, losing the auction feels like a loss in the product dimension and a gain in money compared to the possibility of winning the auction — and it is not possible for the bidder to eliminate losses on both dimensions simultaneously.[15] In an auction with induced monetary values, instead, losing the auction always feels like a loss compared to the possibility of winning the auction. As shown by Lange and Ratan (2010), in the unique monotone symmetric equilibrium a bidder of type θ bids according to the following bidding function:

$$\beta_{IV}^{*}(\theta) = \theta.$$

Therefore, in induced-value auctions the equilibrium behavior of a loss-averse bidder coincides with that of the "classical" model.[16] Hence, we should observe (even loss-averse) subjects bidding the same amount irrespective of the intensity of competition.

3 Experimental Design

The unique prediction of the KR model in second-price auctions with private values is that average bids in real-object auctions should decrease with the number of auction participants while bids in induced-value auctions should not be influenced by the number of participating bidders. We tested this theoretical prediction in a controlled experiment. The experiment involved an auction task and an individual decision-making task.

In the auction task, each participant in our study took part in twelve second-price auctions: three auctions for each prize and four prizes in total. Specifically, for each prize, each participant took part in: a second-price auction with two competitors ($n = 3$), a second-price auction with five competitors ($n = 6$) and a second-price auction with eleven competitors ($n = 12$). The prize that the participant bid on and the total number of people participating in the auction changed randomly from one auction to another. Manipulating the

[15] Unless he submits a bid equal to zero. In equilbrium, however, when $\Lambda \leq 1$ such a bid can only be placed by a bidder with $\theta = 0$.

[16] Notice however that in the classical expected-utility framework bidding one's own value is a (weakly) dominant strategy for a bidder, but this is no longer true with expectations-based loss aversion.

number of auction participants allowed us to test our main hypothesis, that is whether the number of bidders in the auction, other things being equal, affects average and individual bids. To cater to different tastes, we included three different real-object prizes: a University of Sydney hoodie, a Logitech Boombox and a voucher for two cinema tickets.[17] As people who are not interested in buying a particular good would simply bid \$0, and therefore be insensitive to the number of people in the auction, we included three different real-object prizes with the intent to increase the chance that each participant would find at least one of the goods desirable. The fourth auctioned prize was a voucher that subjects could redeem for a prespecified dollar amount. Monetary values $x \overset{U}{\sim} \{\$1, \$2\$, 3, ..., \$29, \$30\}$ were drawn independently across subjects.[18] A subject's value $\$x$ for the voucher stayed constant throughout the experiment. Subjects' own monetary values were their private information, but the distribution of values was common knowledge. Each participant bid three times for every prize, once for each auction size, for a total of twelve auctions.

In the beginning of each auction, participants were told what prize they were bidding on (University of Sydney hoodie, Logitech Boombox, voucher for two cinema tickets, or a money voucher) and how many people in total were participating in the auction (three, six or twelve). After the participant submitted his/her bid in an auction, the program automatically moved on to the next auction without providing any feedback on the auction outcome. We did not provide feedback because we wanted to ensure that participants considered each auction to be independent from the others.[19]. For each auction, participants were given a \$30 endowment that they could use to bid in the auction and were allowed to bid any integer amount between \$0 and \$30. Their budget in each auction was always \$30 and the money saved in one auction could not be rolled over to the next one. Therefore, the auctions were independent in terms of budget constraint: whatever happened in one auction had no monetary consequences for the other auctions. Participants submitted their bids privately using a computer interface. Figure 2 shows an example of a decision screen.

We run a total of eight sessions. Twelve participants took part in each session resulting in a total of twenty-eight auctions run in each individual session: four auctions with all twelve participants (one for each prize), eight auctions with six participants (two for each prize) and sixteen auctions with three participants (four for each prize). Groups of participants in each auction were selected at random and participants did not know the identity of people whom they were bidding against. The order of the auctions was randomized independently for every participant. Participants knew that at the end of the experiment one of the twenty-

[17]At the time of the experiment, the market prices of the products were \$49.95, \$49.95 and \$39, respectively.

[18]Throughout the paper the symbol \$ denotes Australian dollars (AUD).

[19]For example, consider the case of a subject who demands only one boombox. Knowing of being the winner in an auction for a boombox, the subject would likely submit a bid equal to zero in any other auction for the same prize. In this case, however, the potential effect that the change in the number of bidders has on the subject's bid would get confounded with the fact that the subject only wants one boombox.

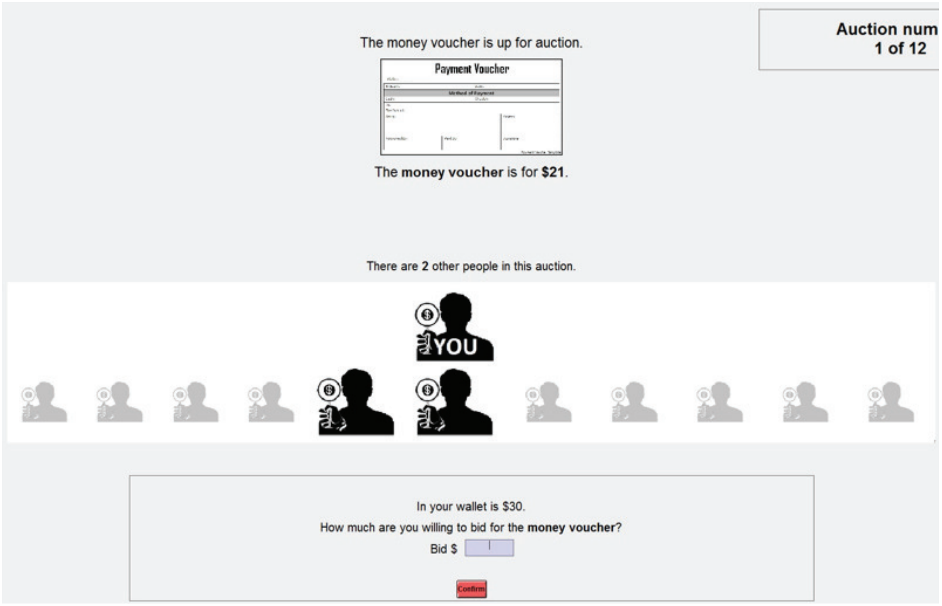


Figure 2: Example of a decision screen. The bidder is bidding for a money voucher valued at $21. Three bidders (including the decision-maker) participate in this auction.

eight auctions that took place during the session would be selected for payment (we call this the payment auction). Subjects who did not participate in this auction received nothing. Subjects who participated in the payment auction but did not win the auction, received the $30 endowment.[20] The participant with the highest bid in the payment auction received the prize and paid for it a price equal to the second-highest bid, leaving him/her with $30 minus the second highest bid in cash, plus the prize.

After the auction task was over subjects completed an independent individual decision-making task with a between-subject design. This task followed the same procedures as in Sprenger (2015) who designed an experiment aimed at distinguishing the KR model from models of Disappointment Aversion (Bell, 1985; Loomes and Sudgen, 1986; Gul, 1991). The exact procedures are explained in Sprenger (2015) and here we just outline the intuition. The task was designed in price list style with 21 decision rows. Each decision row was a choice between a certain amount and a gamble. In each session, subjects were randomly separated into two groups. Half the subjects were asked a series of certainty equivalents for a fixed gamble while the other half were asked a series of probability equivalents for a fixed certain amount. Crucially, the fixed option (the gamble in one case and the certain amount in the other) was always displayed on the left. Sprenger (2015) argues that the option presented on the left becomes a reference point against which the other option is compared. The unique prediction of the KR model is that people will be risk-averse when the reference point is

[20]It it important to highlight that a losing bidder in the payment auction still received the $30 endowment. We decided to do so, and stressed this feature of the payment rule during the instructions-reading phase of the experiment, because we wanted subjects to realize that winning (resp. losing) the auction implies a loss of money (resp. product) and a gain of product (resp. money).

a certain amount and risk-neutral when the reference point is a gamble. Thus comparing choices in these two treatments allows us to perform a test of the KR model of expectations-based reference-dependent preferences at the population level. Our participants completed Conditions 1.1 and 2.1 of the Sprenger (2015) task. See Figure 5 in Appendix A or Table 1 in Sprenger (2015). All participants were paid according to one randomly selected choice from the task.

After completing the individual decision-making task, subjects answered a short questionnaire (for questions see Appendix D). The total earnings for participation in the study were given by the sum of a \$10 show up fee, earnings in the auction task and earnings in the individual decision-making task. On average participants earned \$46 for their participation.[21]

Before completing each task, participants received detailed instructions (available in Appendix B). To make sure that the rules of the second-price auction were clear to everybody, each participant had to answer detailed comprehension questions before starting the task. If a participant failed a question (or part of it), the experimenter explained the task verbally and gave the participant a second set of comprehension questions to complete. Most participants answered all the questions correctly at the first attempt. All of them answered them correctly within two attempts. Comprehension questions are available in Appendix C.

A total of 96 participants (42 males, average age: 22 +/-3.46 SD) took part in the study. The experiment took place in the experimental laboratory at the University of Sydney between May and June 2015. The protocol was approved by the Human Ethics Research Committee at the University of Sydney. The study was implemented using ZTree (Fischbacher, 2007) and subjects were recruited via ORSEE (Greiner, 2015).

4 Results

Overall participants bid sizeable amounts on each of the goods and there was substantial variation between individuals in how much they bid on each of the items as shown in the left and middle column of Table 1. Given the predictions of our theoretical framework, in

[21]In both the auction task and the individual decision-making task, subjects were randomly paid for one of their choices. This random-lottery incentive mechanism, which is widely used in experimental economics, introduces a compound lottery in the decision environment. While this is inconsequential for a decision-maker under standard expected utility, because of the reduction of compound lotteries property, the randomization introduces some further complications in the KR framework as it creates a potential link between choices and reference points across tasks. Yet, the random-lottery incentive mechanism is innocuous also in the KR framework as long as subjects "narrowly bracket "and consider each decision in isolation (see Tversky and Kahneman, 1981 and Rabin and Weizsäcker, 2009). While we cannot ensure that our subjects did indeed consider each auction in isolation, we notice that the order of auctions was random across subjects and no outcome was revealed until the end of the experiment. As for the individual decision-making task, in a series of experiments involving decisions over risky prospects, Starmer and Sudgen (1991) and Cubitt *et al.* (1998) provide evidence that in practice subjects treat these decisions effectively in isolation.

this section we test two main hypotheses about participants' bids:

Hypothesis 1 *Participants' bids in real-object auctions depend on the number of bidders. Specifically, the more participants there are in the auction, the lower the bids are.*

Hypothesis 2 *Participants' bids in the induced-value auctions are not influenced by the number of bidders.*

We then test an additional hypothesis to verify whether our participants' risk preferences are consistent with the KR model using a price list task developed by Sprenger (2015).

Hypothesis 3 *Participants show an endowment effect for risk.*

4.1 Real-Object Auctions Results

As a first test of whether participants changed their bids for the same good when the number of competitors in the auction changes, for each participant we calculated the standard deviation of his/her bid separately for each good. This gave us a total of four standard deviation indexes for each participant, one for each good. If participants bid always the same amount on the same good, this index should be equal to zero. To the contrary, the standard deviation of individual's bids for one particular good is on average equal to 2.43. It is the smallest for the money voucher (1.64) and largest for boombox (2.88). The right column of Table 1 lists average individual standard deviations for each good.

Table 1: Summary statistics of bids for each good

	mean	**sample SD**	**within individual SD**
movie tickets	15.72	9.62	2.09
boombox	19.22	10.51	2.88
hoodie	17.76	10.68	2.36
money voucher	14.04	9.69	1.64

In line with Hypothesis 1, average bids for movie tickets, boombox and hoodie declined as the number of participants in the auction increased from three to twelve (Table 2). For movie tickets and boombox, the average bid also declined when the number of participants increased from three to six. For the hoodie auctions, we actually find that the average bid is non-monotonic in the number of bidders as it increases when the number of bidders increases from three to six and then it decreases when the number of bidders increases to twelve. This non-monotonicity is rather interesting and is not inconsistent with the KR model.[22] Notice instead that average bids for the money voucher do not vary with auction size.

Table 2: Mean bid by good and auction size

	3 participants	**6 participants**	**12 participants**
movie tickets	16.10	15.93	15.12
boombox	19.70	19.32	18.64
hoodie	18.04	18.21	17.02
money voucher	14.02	14.06	14.05

To verify whether the relationship between bids and the number of auction participants is significant, we regressed individual bids on auction size dummy variables separately for each good using a random effects model (see Table 3).[23] Consistent with Hypothesis 1 individuals bid significantly more for movie tickets and hoodie in auction with three bidders as compared to the auction with twelve bidders. While the coefficient for the boombox is the highest, it misses significance.

The analysis in Table 3 is quite strict in the sense that it pools together individuals who might have been not interested in buying at all with those who wanted to make a purchase. Typically when people bid in auctions they are more interested than not in purchasing the product on sale. The potential presence of non-serious bidders in our sample likely dilutes the effects that the number of auction participants has on the bids of real (that is interested) bidders. Therefore, as a next step, we divided the sample into two groups: those who had and those who did not have interest in buying each of the goods. We captured individuals' desire to purchase with a self-reported rating of their desire to buy each of the goods (measured on a scale from 1 to 6). The average desire to buy the movie tickets (boombox, hoodie, and voucher) was equal to 3.3 (3.6, 3.7, and 4.15, respectively). We classified individual-good pairs as (not) having desire to purchase if the desire rating was 4, 5 or 6 (1, 2 or 3). Then we estimated the same random effects model separately for these two groups.

The individuals who indicated desire to buy the good bid significantly more in the three-bidder auction than in the twelve-bidder auction (Table 4). This holds for all the goods that we used in the experiment: movie tickets, boombox and hoodie. Participants also bid more for movie tickets and hoodie in six-bidder auction than in the twelve-bidder auction.

[22]Recall that bidders with high values might increase their bids when competition becomes fiercer. Hence, this observed non-monotonic pattern suggests the presence among our subjects of some bidders with moderate to high values for the hoodie.

[23]According to the Hausman test, the random effects model is more appropriate to analyze our data than the fixed effects model. There are significant differences in bids across individual-good pairs, indicating we should use random effects rather than a simple OLS regression ($\chi^2 = 837.84$, $p < 0.001$, Breusch-Pagan Lagrange multiplier test).

Table 3: Effect of auction size on bids. 3 participants (6 participants) is an indicator variable equal to one when the participant is bidding in an auction with 3 (6) bidders. The reference category is auction with 12 bidders. Subject-good random effects included. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

	movie tickets Coef./se	boombox Coef./se	hoodie Coef./se	money voucher Coef./se
3 participants	0.99**	1.06	1.02*	–0.03
	(0.50)	(0.71)	(0.57)	(0.47)
6 participants	0.81	0.68	1.19**	0.02
	(0.50)	(0.71)	(0.57)	(0.47)
constant	15.11***	18.64***	17.02***	14.05***
	(0.98)	(1.08)	(1.09)	(0.99)
No. of obs	288	288	288	288

Table 4: Effect of auction size on bids for bidders who desire to purchase. 3 participants (6 participants) is an indicator variable equal to one when the participant is bidding in an auction with 3 (6) bidders. The reference category is auction with 12 bidders. Subject-good random effects included. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

	movie tickets Coef./se	boombox Coef./se	hoodie Coef./se	money voucher Coef./se
3 participants	1.84***	1.68*	2.35***	0.02
	(0.57)	(0.96)	(0.91)	(0.62)
6 participants	1.27**	0.68	2.31**	–0.07
	(0.57)	(0.96)	(0.91)	(0.62)
constant	19.78***	23.35***	22.06***	16.93***
	(1.12)	(1.11)	(1.11)	(1.13)
No. of obs	147	165	162	204

Table 5: Effect of auction size on bids for bidders who do not desire to purchase. 3 participants (6 participants) is an indicator variable equal to one when the participant is bidding in an auction with 3 (6) bidders. The reference category is auction with 12 bidders. Subject-good random effects included. $^{*}p < .10,^{**}p < .05,^{***}p < .01$

	movie tickets Coef./se	boombox Coef./se	hoodie Coef./se	money voucher Coef./se
3 participants	0.11	0.22	–0.69	–0.14
	(0.84)	(1.07)	(0.54)	(0.57)
6 participants	0.34	0.68	–0.24	0.21
	(0.84)	(1.07)	(0.54)	(0.57)
constant	10.26***	12.32***	10.55***	7.04***
	(1.23)	(1.51)	(1.33)	(1.29)
No. of obs	141	123	126	84

Among those who were not interested in purchasing the items, we find that the number of participants in the auction had no effect on the bids (Table 5).

A substantial fraction of bids (17%) in our sample were equal to the maximum allowable bid of $30, suggesting the possibility that some bidders might have felt budget-constrained in some auctions. Therefore, to account for the censored nature of the data we have also estimated a Tobit random effects model. The estimation results, available in Table 8 in Appendix A, are all qualitatively similar to the findings presented above. Therefore, we conclude that our experimental evidence supports Hypothesis 1.

Result 1 *Participants on average bid less in real-object auctions as the number of auction participants increases.*

It is important to remark that our findings cannot be rationalized by alternative models of choice under uncertainty, like regret or ambiguity aversion, nor by a model of less-than-fully-rational bidders like the level-k model. Furthermore, the two leading hypotheses that have been put forward to rationalize the extensive volume of overbidding observed in most experimental second-price auctions, that is the spite hypothesis and the "joy of winning" hypothesis, cannot explain these results either. Indeed, while these hypotheses predict that bidders would bid more than their intrinsic value in a second-price auction, the amount of overbid is independent of the number of bidders in the auction. Hence, all these alternative models, like the classical one, do not predict that individual bids should vary with the intensity of competition in the auction.

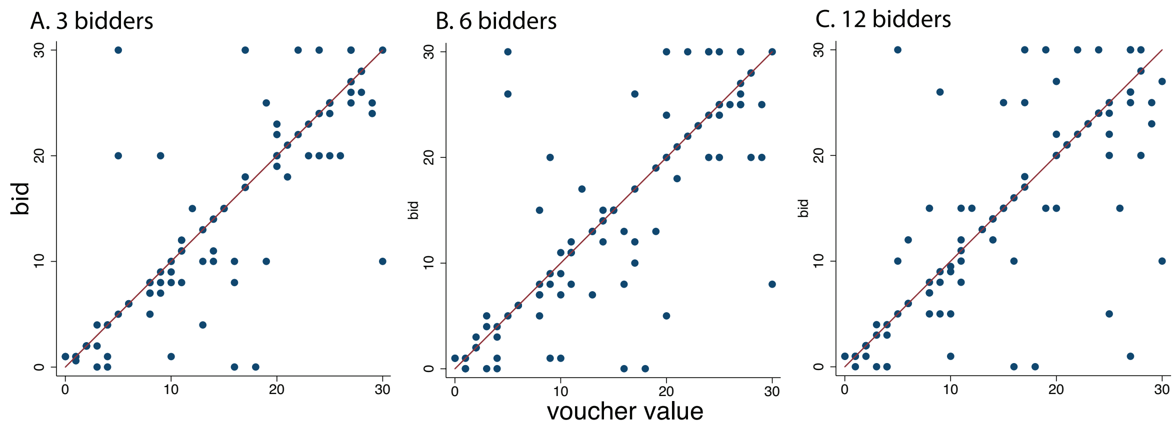


Figure 3: Individual bids for money vouchers plotted against the induced voucher value.

4.2 Induced-Value Auctions Results

According to Hypothesis 2, the number of rivals should not have a significant effect on bids in the induced-value auctions. In line with this hypothesis, the standard deviation in individual bids is the smallest for the money voucher (right column in Table 1). In addition, the mean bid for the money voucher in our sample does not significantly change as the number of bidders increases (Table 2 and Table 3). There is no effect even for those participants who expressed high desire to purchase the money voucher (Table 4).

Regressing bids on the induced values we find that the correlation between the two is highly significant. The coefficient on the voucher value is equal to 0.89 (resp. 0.87 and 0.81) in auctions with three (resp. six and twelve) bidders, all with $p < 0.001$. Figure 3 plots individuals' bids against the value of their vouchers for each auction size. If subjects bid amounts exactly equal to the induced value of their money voucher, all of the bids should fall on the 45-degree lines. Averaging across all auction sizes, we find that 39.93% of the bids were equal to the voucher value, 38.19% of bids were below the voucher value and the remaining 21.86% were above it. This fraction of value-bidding is in line with previous experimental findings. For instance, Kagel and Levin (1993) found 27% of value-bidding, 5.7% of underbidding and 67.2% of overbidding. In Cooper and Fang (2008) and Garratt *et al.* (2012) the same figures were: 44%; 16% and 40%, and 21.2%, 41.3% and 37.5%, respectively. Banerji and Gupta (2014) report 60% value-bidding with the remaining 40% of bids being evenly divided between underbidding and overbidding.[24] Hence, like in Garratt *et al.* (2012), in our experiment we observe more underbidding than overbidding. Overall, we conclude that the experimental evidence supports Hypothesis 2:

Result 2 *The number of participants does not affect bids in induced-value auctions.*

[24]Recall, however, that Banerji and Gupta (2014) look at the BDM mechanism where a single agent bids against a random computer draw and, therefore, strategic interaction is not at play.

4.3 Individual level results

Now we turn to test whether our hypotheses hold also at the individual level. As could be expected, there is significant heterogeneity in how participants responded to changes in the number of bidders in the auction. There are even some who always bid the same amount for some goods, irrespective of the intensity of competition. On average participants changed their bid at least once for 2.36 (out of four) prizes as the number of auction participants changed. Moreover, 14.58% of the participants never changed their bid, 14.58% changed it for one prize, 23.96% for two prizes, 15.63% for three prizes and 31.25% for all four prizes (including the money voucher). In line with Hypothesis 2, participants changed their bids the least often for the money voucher. Table 6 lists for each good how many subjects decreased, increased or did not change their bids as the auction size changed. For example, considering auctions for the movie tickets, from Table 6 we see that 31 (resp. 26, 39) participants decreased (resp. increased, did not change) their bid in auction with twelve bidders as compared to their bid in an auction for the same product with only three bidders. Focusing on bid changes between three-bidder and twelve-bidder auctions, we find that 54% of the subjects did not change their bid for the money voucher between three-bidder and twelve-bidder auctions. The fraction of subjects who bid the same amount of money in three-bidder and twelve-bidder auctions for movie tickets, boombox and hoodie is significanlty lower (40%, 39% and 48% respectively). Similar patterns were observed when the auction size changed from three to six and from six to twelve (see Table 6).

Table 6: Number of participants that increase (↑), decrease (↓) or keep their bid constant (-) as number of participants changes

	3 to 12			3 to 6			6 to 12		
	↓	↑	-	↓	↑	-	↓	↑	-
movie	31	26	39	26	22	48	25	23	48
boombox	26	32	38	22	31	43	24	23	49
hoodie	23	26	47	19	26	51	22	24	50
voucher	18	25	53	15	21	60	18	24	54
total	98	109	177	82	100	202	89	94	201

Interestingly, and seemingly contrary to our hypothesis, not all participants decreased their bids as the number of bidders in the auction increased. It is clear from Table 6 that the number of people who decrease their bid as competition in the auction increases is not overwhelmingly larger than the number of those who do the opposite. What explains our aggregate results in the preceding section is that on average the increases in bids were much smaller than decreases in terms of dollar amounts (see Table 7). A one-sided t-test reveals that the difference between the bids in twelve-bidder and three-bidder auctions is significantly lower than zero for movie tickets ($p = 0.05$), boombox ($p = 0.07$) and hoodie ($p = 0.07$), indicating that people bid significantly less in twelve-bidder auctions than in three-bidder auctions for these goods. We find similar significant effects for a change from six to twelve bidders in auctions for movie tickets ($p = 0.07$) and hoodie ($p = 0.03$). As predicted, the difference between bids in twelve-bidder and three-bidder auctions for the money voucher is never significantly different from zero ($p = 0.95$).

As further evidence that our subjects behaved differently in induced-value auctions than in real-object ones, using the Pearson χ^2 test we confirmed that the frequency distribution of bid changes for the money voucher presented in the first column of Table 6 is different from the frequency distributions of bid changes for the movie tickets and boombox ($\chi^2 = 5.599$ $p = 0.061$ and $\chi^2 = 4.787$ $p = 0.091$, respectively).

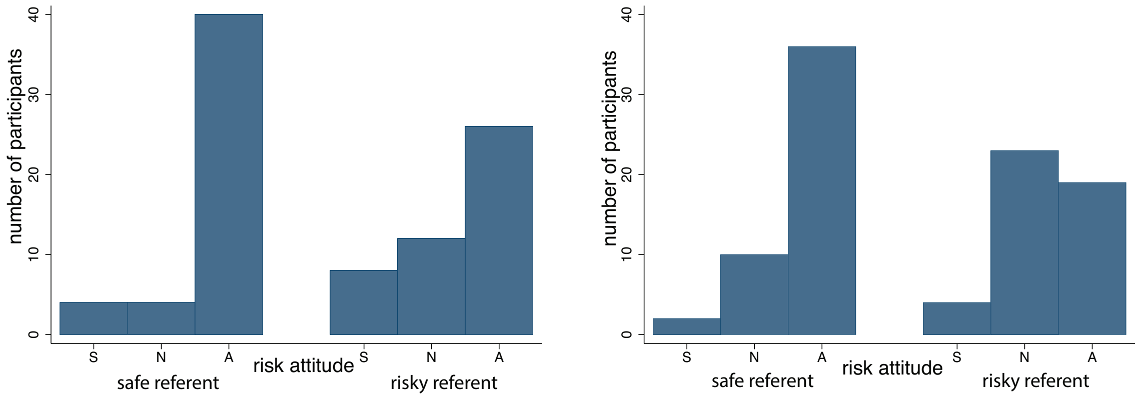
Table 7: Changes in bids (in AUD) as the number of auction participants changes, conditional on participants' decreasing (↓) or increasing (↑) their bid. Average is the sample average. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ in a one sided t-test testing whether the average difference between the bids is smaller than zero

	3 to 12			3 to 6			6 to 12		
	↓	↑	average	↓	↑	average	↓	↑	average
movie	-6.58	4.19	-0.99*	-3.54	3.41	-0.18	-6.68	3.87	-0.81*
boombox	-9.08	4.20	-1.06*	-7.91	4.45	-0.38	-8	5.5	-0.68
hoodie	-9.70	4.81	-1.02*	-4.15	3.67	0.17	-9.71	4.13	-1.19**
voucher	-5.37	3.98	0.03	-4.71	3.57	0.04	-6.44	4.77	-0.01

4.4 Endowment effect for risk

Finally, we tested whether participants in our study display a behavior consistent with the KR model in an unrelated, individual decision-making task. In each session, subjects were randomly assigned to one of two groups. Half of the subjects were asked a series of certainty equivalents for a given binary gamble. In each decision the gamble was fixed while the certain amount was changed. The other half were asked a series of probability equivalents for given a certain amount. In each decision the certain amount was fixed while the binary gamble probabilities were changed. Köszegi and Rabin's (2006, 2007) model of expectations-based reference-dependent preferences makes the unique prediction that people exhibit an endowment effect for risk (Sprenger, 2015). In particular, when the reference point is stochastic, and an individual is offered a certain amount, the KR model predicts near risk neutrality; conversely, when the reference point is a fixed certain amount, and an individual is offered a gamble, the KR model predicts risk aversion.

In figure 4 we classify each participant into one of three risk-attitude types: risk seeking



(a) Risk Attitude Classification

(b) Risk Attitude Classification - Wide Interval

Figure 4: Classification of participants into risk seeking "S", risk neutral "N" and risk averse "A" based on their lottery choices. Participants with multiple switching points are excluded. Subfigure (a) is based on the classifications using the interval of a participant's switch point. Subfigure (b) is based on a wider interval classification including the switch point +/- one choice.

(S), risk neutral (N) and risk averse (A) using individuals' switching points as the classification criterion. Then, separately for each set of questions, we counted how many subjects fell in each category. Figure 4 (a) shows the results. We find that the number of subjects that are classified as risk averse is significantly larger when the fixed option was the certain amount than when the fixed option was the gamble. As this classification of responses is rather strict, following Sprenger (2015) we then re-classified each participant's risk-attitude type by using a wider interval for risk neutrality. Under this classification, individuals are classified as risk-neutral if their switching point interval includes risk neutrality or if it is one row above or below. The results are shown in 4 (b). Just as in Sprenger (2015), we find that also under this less strict classification the number of subjects classified as risk averse when the fixed option was the certain amount is significantly larger than when the fixed option was the gamble. Moreover, when the fixed option is the gamble the majority of subjects are now classified as risk neutral. Therefore, we conclude that also in this independent task subjects in our study behaved consistently with the predictions of the KR model.

Result 3 *Participants show an endowment effect for risk consistent with the KR model.*

5 Discussion and Conclusion

We presented results from a laboratory experiment with a within-subject design aimed at testing a unique comparative static prediction of the KR model in second-price auctions. Our results are supportive of the KR model. In real-object auctions, we find that subjects' bids are affected by the number of competitors and, on average, they decline with the intensity of competition. In induced-value auctions, instead, bids are unaffected by the intensity of competition. These results also show that people behave differently in auctions for real objects than in auctions with induced monetary values, casting some doubts on the extent to which conclusions drawn from laboratory auctions with induced valuations can be extended to real-object auctions in the field. We conclude the paper by discussing some limitations of our design as well as possible directions for future research.

As the KR model makes different predictions for real-object auctions vs. induced-value one, we had subjects participating in both. While conducting real-object auctions in the laboratory opens the door to considering many new interesting questions, it also has some drawbacks. In particular, we cannot pin down what subjects' intrinsic value for a product is. Indeed, as argued by Banerji and Gupta (2014) and others, estimates of WTP that are derived using the conventional BDM mechanism are likely to be significantly biased if agents are loss-averse.[25] Moreover, as it is not possible to directly observe (and control for) subjects' intrinsic values, one possible concern in our experiment is the possibility that in real-object auctions subjects have interdependent or common values. While we cannot completely remove this concern, we notice that the interdependent or common-value model usually applies to goods whose objective quality or value is uncertain and for which bidders might have access to different sources of information. In our experiment most of the subjects were familiar with the products we used and they all had the same opportunity to inspect the products before the auctions began.[26]

Another possible concern when using real goods is the possibility of resale. We could have avoided this problem by auctioning off some immediate consumption good, like a chocolate bar or a sandwich. However, we chose to use durable, somewhat expensive items to cater to different tastes and also to increase the chance that subjects in our experiment would find at least one of the items to be appealing. If subjects were only interested in the items we selected for the purpose of reselling them, then they should have bid for them like they bid for money vouchers. The fact that the observed bidding behavior in real-object auctions was significantly different than the bidding behavior in the induced-value auctions suggests that resale is not a major concern for our experiment.

Besides providing support for the KR model, our experimental results also have potentially interesting implications for auction design. Bulow and Klemperer (1996) showed that when bidders have standard preferences an auction with $n + 1$ bidders and no reserve price (also known as an "absolute" auction) yields a higher expected revenue than an auction with

[25]To the best of our knowledge, no incentive-compatible way to estimate subjects' intrinsic values under loss aversion has been derived so far.

[26]Of course prior inspection was not possible for the movie tickets. However, the instructions, read before the auctions began, explained that e-tickets would be sent via email at the end of the experiment. Subjects could decide later when to go to the movies and what show to see. These were two admissions for the same standard movie session of choice to enjoy at several movie theaters located in the Sydney metropolitan area. The tickets were valid for six months.

n bidders and an optimally chosen reserve price. Hence, when facing the choice between introducing a reserve price or inviting an additional bidder into the auction, a revenue-maximizing seller should always pick the latter. Our results, however, suggest that this might not be the case if bidders are expectations-based loss-averse as increasing competition in the auction might induce (at least some) bidders to bid less aggressively. Notice though that our experiment shows that average bids decline with the intensity of competition; yet the effect on the seller's revenue depends on how competition would affect the second-highest bid. Analyzing how reserve prices and varying the number of bidders might affect revenue when bidders are loss-averse is an interesting question left for future research.

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A Appendix: Tables and Figures

Table 8: Tobit analysis of the effect of auction size on bids. 3 participants (6 participants) is an indicator variable equal to one when the participant is bidding in an auction with 3 (6) bidders. The reference category is auction with 12 bidders. Right-censored at bid=30. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$

	movie tickets Coef./se	boombox Coef./se	hoodie Coef./se	money voucher Coef./se
3 participants	1.17**	1.29	1.18*	-0.05
	(0.56)	(0.94)	(0.71)	(0.51)
6 participants	0.86	0.88	1.45**	0.03
	(0.56)	(0.94)	(0.71)	(0. 51)
constant	15.67	20.97	19.07	14.39
	(1.11)	(1.48)	(1.49)	(1.06)
No. of obs	288	288	288	288

Panel A: Probability Equivalent

	Option A: Certain Payment of $10		*or*	Option B: Chance of $0	Chance of $30	
1)	$10	☐	*or*	100 in 100	0 in 100	☐
2)	$10	☐	*or*	95 in 100	5 in 100	☐
3)	$10	☐	*or*	90 in 100	10 in 100	☐
4)	$10	☐	*or*	85 in 100	15 in 100	☐
5)	$10	☐	*or*	80 in 100	20 in 100	☐
6)	$10	☐	*or*	75 in 100	25 in 100	☐
7)	$10	☐	*or*	70 in 100	30 in 100	☐
8)	$10	☐	*or*	65 in 100	35 in 100	☐
9)	$10	☐	*or*	60 in 100	40 in 100	☐
10)	$10	☐	*or*	55 in 100	45 in 100	☐
11)	$10	☐	*or*	50 in 100	50 in 100	☐
12)	$10	☐	*or*	45 in 100	55 in 100	☐
13)	$10	☐	*or*	40 in 100	60 in 100	☐
14)	$10	☐	*or*	35 in 100	65 in 100	☐
15)	$10	☐	*or*	30 in 100	70 in 100	☐
16)	$10	☐	*or*	25 in 100	75 in 100	☐
17)	$10	☐	*or*	20 in 100	80 in 100	☐
18)	$10	☐	*or*	15 in 100	85 in 100	☐
19)	$10	☐	*or*	10 in 100	90 in 100	☐
20)	$10	☐	*or*	5 in 100	95 in 100	☐
21)	$10	☐	*or*	0 in 100	100 in 100	☐

Panel B: Certainty Equivalent

	Option A: Chance of $0	Chance of $30		*or*	Option B: Certain Amount	
1)	50 in 100	50 in 100	☐	*or*	$0.00 with certainty	☐
2)	50 in 100	50 in 100	☐	*or*	$0.50 with certainty	☐
3)	50 in 100	50 in 100	☐	*or*	$1.00 with certainty	☐
4)	50 in 100	50 in 100	☐	*or*	$1.50 with certainty	☐
5)	50 in 100	50 in 100	☐	*or*	$2.50 with certainty	☐
6)	50 in 100	50 in 100	☐	*or*	$3.50 with certainty	☐
7)	50 in 100	50 in 100	☐	*or*	$4.50 with certainty	☐
8)	50 in 100	50 in 100	☐	*or*	$6.50 with certainty	☐
9)	50 in 100	50 in 100	☐	*or*	$8.50 with certainty	☐
10)	50 in 100	50 in 100	☐	*or*	$10.50 with certainty	☐
11)	50 in 100	50 in 100	☐	*or*	$13.50 with certainty	☐
12)	50 in 100	50 in 100	☐	*or*	$16.50 with certainty	☐
13)	50 in 100	50 in 100	☐	*or*	$19.50 with certainty	☐
14)	50 in 100	50 in 100	☐	*or*	$21.50 with certainty	☐
15)	50 in 100	50 in 100	☐	*or*	$23.50 with certainty	☐
16)	50 in 100	50 in 100	☐	*or*	$25.50 with certainty	☐
17)	50 in 100	50 in 100	☐	*or*	$26.50 with certainty	☐
18)	50 in 100	50 in 100	☐	*or*	$27.50 with certainty	☐
19)	50 in 100	50 in 100	☐	*or*	$28.50 with certainty	☐
20)	50 in 100	50 in 100	☐	*or*	$29.00 with certainty	☐
21)	50 in 100	50 in 100	☐	*or*	$29.50 with certainty	☐
22)	50 in 100	50 in 100	☐	*or*	$30.00 with certainty	☐

Figure 5: A list of choices in the lottery task. Half of the participants were shown Panel A and the other half Panel B questions. Reprinted from Sprenger (2015).

B Appendix: Instructions

General Instructions

You are participating in an experiment on economic decision-making and will be asked to make a number of choices. If you follow the instructions carefully, you can earn some money and goods. At the end of the experiment, you will be paid your earnings.

You are not allowed to communicate with other participants. If you have a question, raise your hand and we will gladly help you.

The study is strictly anonymous: that is, your identity and actions will not be revealed to others and the identity and actions of others will not be revealed to you.

The study consists of the following parts:

1. Instructions
2. Comprehension test
3. Auction task
4. Decision task
5. Questionnaire about you and the study
6. Receipts, payment and good-bye!

Your final payment will be determined by the choices that you make in the experiment so please pay attention to your decisions. Once you make a selection and move on to the next stage you will not be allowed to go back and change your selection. So, please really pay attention to your decisions.

You will receive a $10 show up fee and throughout the experiment you can make more money or lose some of it.

Your final earnings = $10 (show up fee) + earnings from auction task + earnings from decision task

Your choices from one part of the experiment will have an impact on earnings ONLY in that part of the experiment. In other words, what you choose to do in the auction task will not influence your payment from the decision task and vice versa.

It may happen in the experiment that you will have to wait for others to finish some tasks before you are allowed to continue. In this case the screen will display the "Please wait" message.

Instructions: Auction task

Today we will conduct 28 auctions in total but each one of you will only participate in 12 of these auctions.

In **each** auction in which you participate, you will receive an endowment of $30 from us to spend. You should think of this as your money. You will then have an opportunity to use this money to bid in the current auction. You cannot save money from one auction to spend in another. Your decision in one auction will not influence how much money you will have to spend in another auction. In each auction, your **budget** is equal to your endowment and you cannot submit a bid larger than your endowment.

In some auctions there will be many people bidding for the same good, while in others, there will be just a few bidders but in each auction, there can be only one winner. At the beginning of each auction, we will inform you about the number of people participating in the auction.

If you purchase a product, it will be a final sale. No returns, exchanges or refunds are possible. Today, you will have an opportunity to bid to win one of the following products:

2 cinema tickets

Take a friend along to see the movie of your choice at your favourite Event, Greater Union, Birch Carroll & Coyle Cinema! Your e-tickets will be sent to you via email at the end of the experiment. You can decide later when to go to the movies and what show you would like to see. These are two admissions for the same standard movie session of choice to enjoy at an Event, Greater Union or Birch Carroll & Coyle across Australia. Valid for 6 months.

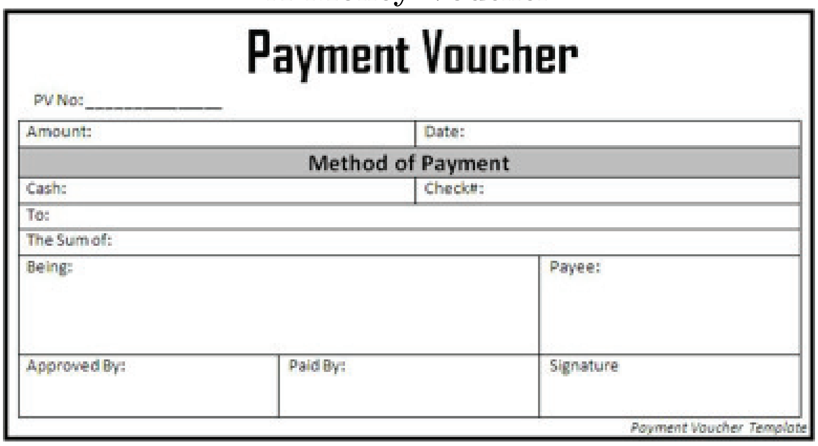
A classic University of Sydney hoodie

If your size available is not available, you will be able to exchange it at the University of Sydney Union shop. Note that our model does not have a zipper.

A White Logitech Mini Boombox

The perfect size to take great sound with you - around the house, over to a friend's, to parties or when you travel! The Logitech Mini Boombox is a mobile speaker and speakerphone that pairs easily with smartphones, tablets and other Bluetooth enabled devices. The specially designed acoustic chamber delivers great sound with enhanced bass, with up to 10 hours playback time. The internal battery is USB-rechargeable, and the device features a handy speakerphone with built in mic for crystal-clear calls.

A Money Voucher



Payment Voucher

PV No:_____________

Amount:	Date:
Method of Payment	
Cash:	Check#:
To:	
The Sum of:	

Being:		Payee:
Approved By:	Paid By:	Signature

Payment Voucher Template

The voucher is redeemable from the experimenter at the end of this experimental session in exchange for cash.

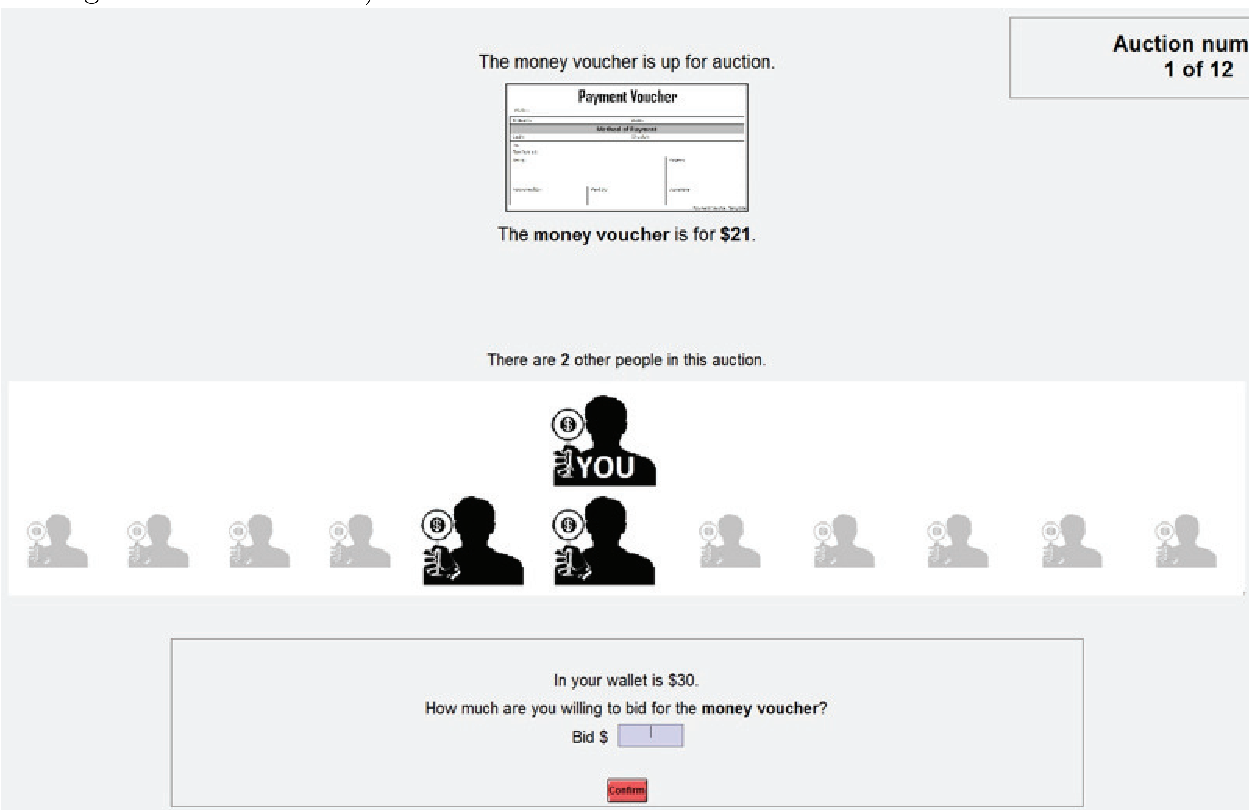
The monetary value of the voucher that you will be bidding on will be randomly selected by the computer at the beginning of this experimental session and will stay the same throughout the experiment. It can be any (integer) amount between \$0 and \$30, with each amount being equally likely to be selected.

The voucher value is selected randomly and independently for each participant so different people in the experiment will be offered vouchers of different value. You will be informed of the exact value of your voucher but not of the values of other people's values.

Remember however that even though you do not know the exact values of other people's vouchers, you know that they are an amount between \$0 and \$30.

Auction task procedure

In the beginning of each auction we will tell you how many other people participate in the auction with you and what good is on offer. If it is a money voucher auction, we will tell you the exact value of your money voucher. In the example below, a money voucher valued to you at \$21 is being auctioned and 3 people are bidding on it. (Notice that the other 2 people who are also bidding on a money voucher will likely have a different dollar value assigned to the voucher.)



Type in your bid and press **Confirm**. How much you bid will never be revealed to others.

After you submit your bid, you will move on to another auction that may have a different good on offer and where you will face a different randomly selected set of bidders. You will not learn the outcome of the auctions until the end of the experiment.

Earnings from the Auction task

When all auctions are finished, the computer will randomly pick one of the 28 auctions from this experimental session. We will call it the "Payout Auction".

Your earnings from the auction task will depend on:

- Whether or not you took part in the Payout Auction, and

- Your bid in the Payout Auction.

Earnings of those who participated in the Payout Auction

All participants in the Payout Auction will be ranked based on the bids that they submitted. The person with the highest bid is the auction winner. The winner will get the good (or the money voucher) and (s)he will pay for it a price equal to the **second highest bid** (not her own bid). If two or more bidders submit the same bid, the computer will randomly select one of them as the winner. The winner's earnings for the auction part of the experiment are calculated according to the following formula:

Earnings of the winner of the Payout Auction = product/voucher + endowment - auction price

(Price paid is equal to the second highest bid in the Payout Auction.)

Everybody else who participated in the Payout Auction keeps their endowment.

Earning of non-winners of the Payout Auction = endowment

Earnings of those who did not participate in the Payout Auction

All those who did not participate in the payout auction (non-participants) receive no additional payment for this task. They do not get any additional money and do not get the product. Earnings of non-participants in the Payout Auction = \$0

You will learn the outcome of the payment auction at the end of the experiment after you finish the questionnaire.

Here are a couple of examples to help you understand the payment rule.

Example 1: Imagine that in the auction selected as Payout Auction we offered a USyd hoodie. All auction participants received an endowment equal to \$30. There were 6 people who participated in this auction. The table below lists their bids:

Participant name	Bid
Participant1	\$20 (price paid)
Participant2	\$19
Participant3	\$7
Participant4	\$3
Participant5	\$12
Participant6 (winner)	\$30 (winner)

Participant6 wins the auction because (s)he entered the highest bid (\$30). (S)he pays \$20 (the second highest bid) for the hoodie. The earning of the winner from the auction task are:

Earnings of the winner = hoodie + \$10

(Endowment - price paid = \$30 - \$20 = \$10)

The earnings from the auction task for other participants in the Payout Auction who did not win is \$30 (endowment).

The earnings from the auction task for people who did not participate in the Payout Auction is \$0.

Example 2: Imagine that in the auction selected as Payout Auction we offered a money voucher. In the beginning of the experiment the computer decided voucher values (between \$0 and \$30) for each of the participants (listed in the column on the right). All auction participants received an endowment equal to \$30. There were 3 people who participated in this auction. The table below lists their bids and values:

Participant name	Bid	Voucher value
Participant1	\$20 (winner)	\$20
Participant2	\$14 (price paid)	\$25
Participant3	\$3	\$7

The winner of this auction is Participant1. (S)he pays \$14 (second highest bid) for a \$20 money voucher. The payout for the winner from the auction task is:

Earnings of the winner (Participant 1): \$36

(Endowment + value for the money voucher - price paid =\$30+\$20 - \$14 = \$36)

The payout from the auction task of other Payout Auction participants (Participant 1 and 2):

Earning of non-winners of the Payout Auction = \$30 (endowment)

The payout from the auction task for people who did not participate in the Payout Auction is \$0.

Note: When you are bidding on a money voucher, you only know how much your voucher is worth to you. You do not know how much it is worth to the other bidders. You only know that other people?s vouchers are worth somewhere between \$0 and \$30.

Instructions: Decision task

In this task, you will make decisions between two options. The first option will always be called OPTION A. The second option will always be called OPTION B. In each decision situation, all you have to do is decide whether you prefer OPTION A or OPTION B.

Throughout the task, either OPTION A or OPTION B will involve chance. You will be fully informed of the chance involved for every decision. For example, OPTION A could be a 40% chance of receiving $30 and a 60% chance of receiving $0.

In this task, most people begin by preferring Option A and then switch to Option B, so one way to view this task is to determine the best row to switch from Option A to Option B.

Payment for Decision task

After you finish submitting all of your choices, the computer will randomly select one of your decisions to count for payment. Each decision has an equal chance of being selected. If you preferred OPTION A, then OPTION A will be implemented. If you preferred OPTION B, then OPTION B will be implemented.

Suppose that the decision selected by the computer to count for payment was a choice between $10 for sure and 40% chance of winning $30. If on that trial you selected $10, you will get it for sure. If on that trial you selected the 40% chance of winning $30, the computer will randomly draw a number between 1 and 100, with each number being equally likely. If the number drawn is less or equal than 40, you will receive $30. If the number drawn is strictly greater than 40, you will receive $0. You will learn the outcome of this task at the end of the experiment when you finish the questionnaire.

Final payment

Your final payment for participation in this study is the sum of the following:

- the participation fee ($10)
- your earnings from the auction task
- your earnings from the decision task.

GOOD LUCK!!!!

PLEASE COMPLETE THE COMPREHENSION QUESTIONS NOW. LET THE EXPERIMENTERS KNOW WHEN YOU ARE DONE BY RAISING YOUR HAND AND WE WILL COME TO CHECK YOUR ANSWERS.

C Appendix: Comprehension questions

C.1 Set one: completed by every participant

Experiment Comprehension Questionnaire

Question 1

Imagine that 12 people participated in the study. Below are the details of the payout auction. There were 6 participants in the payout auction. They were bidding on 2 cinema tickets and each had $30 endowment in his/her wallet.

Participant name	Bid
Participant3	$25
Participant5	$20
Participant6	$27
Participant7	$3
Participant9	$12
Participant12	$1

a) Who wins the auction?

- Participant 3
- Participant 5
- Participant 6
- Participant 7
- Participant 9
- Participant 12

b) How much does (s)he pay for the tickets?

- $0
- $20
- $25
- $27

c) What are the earnings of Participant3 from this part of the experiment?

- $0 + cinema tickets
- $5 + cinema tickets

- $27
- $30

d) What are the earnings of Participant5 from this part of the experiment?

- $0 + cinema tickets
- $5 + cinema tickets
- $27
- $30

e) What are the earnings of Participant6 from this part of the experiment?

- $0 + cinema tickets
- $5 + cinema tickets
- $27
- $30

f) What are the earnings of Participant2 from this part of the experiment?

- $0
- $20
- $27 + cinema tickets
- $30 + cinema tickets

Question 2

Imagine that 12 people participated in the study. Below are the details of the payout auction. There were 3 participants in the payout auction. They were bidding on money vouchers and each had $30 endowment in his/her wallet.

Participant name	Bid	Voucher value
Participant3	$17	$17
Participant5	$12	$12
Participant12	$20	$22

a) Who wins the auction?

- Participant3
- Participant5
- Participant12

b) How much does (s)he pay for the voucher?

- $8
- $12
- $17
- $20

c) What are the earnings of Participant3 from this part of the experiment?

- $0
- $17
- $30
- $35

d) What are the earnings of Participant5 from this part of the experiment?

- $0
- $17
- $30

- \$35

e) What are the earnings of Participant12 from this part of the experiment?

- \$0
- \$17
- \$30
- \$35

f) What are the earnings of Participant6 from this part of the experiment?

- \$0
- \$17
- \$30
- \$35

Question 3
The final payout from the experiment is the sum of (check all that apply):

- \$10 show up fee
- earnings from the auction task
- earnings from the decision task
- each participant gets one of the products for sure

C.2 Set two: used only in case of an error in set one

Experiment Comprehension Questionnaire

Question 1a

Imagine that 12 people participated in the study. Below are the details of the payout auction. There were 6 participants in the payout auction. They were bidding on 2 cinema tickets and each had $30 endowment in his/her wallet.

Participant name	Bid
Participant2	$25
Participant5	$20
Participant6	$17
Participant8	$9
Participant9	$12
Participant11	$30

a) Who wins the auction?

- Participant2
- Participant5
- Participant6
- Participant8
- Participant9
- Participant11

b) How much does (s)he pay for the tickets?

- $0
- $17
- $20
- $25

c) What are the earnings of Participant2 from this part of the experiment?

- $0
- $5 + cinema tickets
- $20 + cinema tickets

- $30

d) What are the earnings of Participant5 from this part of the experiment?

- $0
- $5 + cinema tickets
- $20 + cinema tickets
- $30

e) What are the earnings of Participant11 from this part of the experiment?

- $0
- $5 + cinema tickets
- $20 + cinema tickets
- $30

f) What are the earnings of Participant10 from this part of the experiment?

- $0
- $5 + cinema tickets
- $20 + cinema tickets
- $30

Question 2a

Imagine that 12 people participated in the study. Below are the details of the payout auction. There were 3 participants in the payout auction. They were bidding on money vouchers and each had $30 endowment in his/her wallet.

Participant name	Bid	Voucher value
Participant2	$15	$22
Participant5	$10	$10
Participant9	$20	$20

a) Who wins the auction?

- Participant2
- Participant5
- Participant9

b) How much does (s)he pay for the voucher?

- $10
- $15
- $20
- $22

c) What are the earnings of Participant2 from this part of the experiment?

- $0
- $30
- $35
- $40

d) What are the earnings of Participant5 from this part of the experiment?

- $0
- $30
- $35
- $40

e) What are the earnings of Participant9 from this part of the experiment?

- $0
- $30
- $35
- $40

f) What are the earnings of Participant12 from this part of the experiment?

- $0
- $30
- $35
- $40

Question 3a
The final payout from the experiment is the sum of (check all that apply):

- $10 show up fee
- earnings from the auction task
- earnings from the decision task
- each participant gets one of the products for sure

D Appendix: Post-experimental questionnaire

1. Age [enter numeric value]
2. Gender [male, female]
3. I am: [undergraduate student, graduate student, postgraduate, employee]
4. What year are you in? [1, 2, 3, 4, 5, 6, does not apply]
5. How much did you want to buy each of the goods? [rating on a scale from 1(=did not want the item at all) to 6 (=really wanted to buy)]
6. How familiar were you with each of the goods before participating in this study? [rating on scale from 1(=I did not hear about the product before) to 6 (=I know this product very well)]
7. Do you own any of these products? [yes/no answer, asked each of the goods separately]
8. What amount of money would make you indifferent between buying and not buying each of the goods? [free entry, asked separately for each of the goods]
9. Please describe your bidding strategy. [free text entry]
10. Did your bidding strategy change throughout the experiment? [free text entry]
11. Did you feel cash-constrained in the auction for product ...? (i.e., Was the endowment you were given not enough?) [yes/no, asked for each good separately]
12. Did you intend to buy the good a) for own use b) as a gift c) to resell d) other? [asked for each good separately]